PARAMETER OPTIMIZATION

OF ELECTRIC VEHICLES

ACCORDING TO DRIVING BEHAVIOR

Ph. D. Dissertation

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PARAMETER OPTIMIZATION OF ELECTRIC VEHICLES ACCORDING TO DRIVING BEHAVIOR

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ABSRACT

PARAMETER OPTIMIZATION OF ELECTRIC VEHICLES ACCORDING TO DRIVING BEHAVIOR

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Department of Electrical and Electronics Engineering
Eskişehir Technical University, Institute of Graduate Programs, November, 2019
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The thesis aims to reduce the environmental and economic losses caused by the use of vehicles. To this end, the drivers are primarily divided into three classes: calm, normal and aggressive. Data were recorded from the test drives conducted with male and female drivers of different ages with vehicle tracking device and smartphone application. With this data, attribute extraction is made and classification accuracy of the drives with different attributes is examined. Support Vector Machine, K-Nearest Neighbor and a hybrid method using the Support Vector Machine and Markov Chain methods were used as classification algorithms, and the drives were divided into the correct classes with an accuracy of 98.9%, 93.3% and 92.2% respectively. The purpose of all these operations is to ensure the correct classification of the drivers from the available data and to optimize the electric vehicle for these drivers. Electric motor has been selected as the component to be optimized so that both battery and vehicle size can be changed. Motor power was determined for all drive classes as a result of optimization using Multiobjective Genetic Algorithm method. Lower engine power means lower battery, smaller car, less production costs, less carbon emissions. Greenhouse gas, which is harmful to nature, is released not only by the burned gasoline, but also during the production phase of the vehicle and the electricity used to charge the battery. With the regulation proposed by the study, economic and environmental important steps are taken by changing the preference of the car.

Keywords: Driver classification, Parameter optimization, Electric vehicle, Support vector machine, Markov chain.

ÖZET

SÜRÜCÜ DAVRANIŞINA GÖRE ELEKTRİKLİ ARAÇLARIN PARAMETRE OPTİMİZASYONU

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Tez çalışmasında araç kullanımının sebep olduğu çevresel ve ekonomik kayıpların azaltılması hedeflenmektedir. Bu amaç doğrultusunda öncelikle sürücüler sakin, normal ve agresif olmak üzere üç sınıfa ayrılmıştır. Farklı yaş dağılımına sahip kadın ve erkek sürücüler ile yapılan test sürüşlerinden araç takip cihazı ve akıllı telefon uygulaması ile veriler kaydedilmiştir. Bu veriler ile öznitelik çıkarımı yapılmış ve farklı özniteliklerle sürücülerin sınıflandırma doğrulukları irdelenmiştir. Destek Vektör Makinesi, En yakın komşuluk ve Destek Vektör Makinesi ile Markov zinciri yöntemlerinden faydalanılan hibrit bir yöntem sınıflnadırma algoritmaları olarak kullanılmış ve sırasıyla % 98.9, %93.3 ve %92.2 doğrulukla sürücüler doğru sınflara ayrılmıştır. Tüm bu işlemlerin amacı eldeki verilerden sürücülerin doğru bir şekilde sınıflandırılmasının sağlanarak bu sürücüler için elektrikli araç optimizasyonu yapabilmektir. Optimizasyon yapılacak bileşen olarak elektrik motoru seçilmiştir bu sayede hem batarya hem de araç boyutu üzerinde değişiklik sağlanabilmektedir. Multiobjective Genetic Algorithm yöntemi kullanılarak gerçekleştirilen optimizasyon sonucunda tüm sürücü sınıfları için motor gücü belirlenmiştir. Daha düşük motor gücü demek daha düşük batarya, daha küçük araba, daha az üretim maliyeti, daha az karbon salınımı anlamına gelmektedir. Sadece yakılan benzin ile değil aracın ve bataryayı şarj etmek için kullanılan elektriğin üretim aşamasında da doğaya zararlı sera gazı salınmaktadır. Çalışmanın önerdiği düzenleme ile araba tercihinin değiştirilmesi ile ekonomik ve çevresel önemli adımlar atılmış olmaktadır.

Anahtar Kelimeler: Sürücü sınıflandırma, Elektrikli araç, Parametre optimizasyonu, Destek vektör makinesi, Markov zinciri

08/11/2019

STATEMENT OF COMPLIANCE WITH ETHICAL PRINCIPLES AND RULES

I hereby truthfully declare that this thesis is an original work prepared by me; that I have behaved in accordance with the scientific ethical principles and rules throughout the stages of preparation, data collection, analysis and presentation of my work; that I have cited the sources of all the data and information that could be obtained within the scope of this study, and included these sources in the references section; and that this study has been scanned for plagiarism with "scientific plagiarism detection program" used by Eskişehir Technical University, and that "it does not have any plagiarism" whatsoever. I also declare that, if a case contrary to my declaration is detected in my work at any time, I hereby express my consent to all the ethical and legal consequences that are involved.

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Tuba Nur SERTTAŞ

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LIST OF ACRONYMS

a	: Acceleration
APU	: Auxiliary Power Unit
$argmax$	: Arguments of the Maxima
BEV	: Battery Electric Vehicle
CARB	: California Air Resources Board
CNG	: Compressed Natural Gas
CO2	: Carbon Dioxide
CTL	: Centre for Transport and Logistics
CV	: Conventional Vehicles
DAGSVM	: Directed Acyclic Graph Support Vector Machine
DP	: Dynamic Programming
EPA	: Environmental Protection Agency
EV	: Electric Vehicle
exp	: Exponantional
f_f	: The Rolling Resistance Coefficient
FC	: Fuel Cell
FCV	: Fuel Cell Vehicle
FC-HEV	: Fuel Cell Hybrid Electric Vehicle
FC-PHEV	: Fuel Cell Plug-in Hybrid Electric Vehicle
FTP	: Federal Test Procedure
g	: The Earth acceleration.
G	: The Weight of the Electric Car
GA	: Genetic Algorithm
GhGs	: Greenhouse Gas
GPS	: Global Positioning System
HEV	: Hybrid Electric Vehicle
HIL	: Hardware-In-the-Loop
HMM	: Hidden Markov Model
HWFET	: Highway Test Conditions
h	: Hour

Hz : Herthz
ICE : Internal Combustion Engine
J : Joule
k_e : The Coefficient of Air Resistance of the Electric Car
kg : Kilogram
KKT : Karush-Kuhn-Tucker
km : Kilometer
kN : KiloNewton
KNN : K Nearest Neighbor
LCA : Life Cycle Assessment
LDA : Linear Discriminant Analysis
Li-ion : Lithium-ion
LPG : Liquefied Petroleum Gas
m^2 : Square Meter
m_{veh} : Vehicle Mass
m_{pt} : Power Train Mass
m_{es} : Energy Storage Mass
m_{gl} :Glider Mass
m_{sup} : Additional Material Mass
MOOP : Multi-Objective Optimization Problem
NEDC : New European Driving Cycle
NiMH : Nickel Metal Hybrid
NYC : New York City
OVR : One-Versus-Rest
OVO : One-Versus-One
P : The Power of the Electric Motor
P_a : Average Power
PHEV : Plug-in Hybrid Electric Vehicle
PSO : Particle Swarm Optimization
PWM : Pulse Width Modulation
QP : Quadratic Programming
rad : Radian
s : Second

S	: The Front Area of the Electric Car
SC	: Supercapacitor
SQP	: Sequential quadratic programming
SVM	: Support Vector Machine
t_a	: Acceleration Time
$tanh$	: Hyperbolic Tangent
v	: Speed
V_f	: Final Speed
V_b	: Base Speed
w	: Angular Velocity
W	: Watt
Δ	: Derivative
δ_a	: The Coefficient of Influence of the Rotating Masses of the Car
3D	: Three Dimensional

1. INTRODUCTION

It is known that the means of transportation of the future will mostly be electric vehicles. Developments in electric vehicles effect our lives not only technologically, but also as environmental changes. Electric vehicles have a low carbon impact as they do not directly cause exhaust emissions, such as vehicles with internal combustion engines. Considering gas emissions on earth, the emission rate caused by transportation is too large to be ignored. This rate will fall to include electric vehicles in daily life. In order to achieve such success, some deficiencies in electric vehicles need to be eliminated. The length of the charging cycle, the inadequacy of the charging stations, the high energy requirements and the short distance are some of the problems to be solved. However, electric vehicle drivers can implement a driving strategy that will positively affect the energy management system. Even without changing the driving style, the electric vehicle capacity dimensioning, which will provide the same experience, can be optimized. At this point, optimum use is possible which allows the driver to request. It is very important to define the behavior of the drivers when considering the basic reasons such as the reduction of energy and carbon emission. This definition also emerges as the basic information needed for such topics as vehicle modeling, reduction of traffic accident, risk analysis, insurance operations. For this reason, researchers have been trying to define drivers and drives in different ways for different purposes. Defining driver behavior is actually the generation of a safety factor for the driver by examining the data obtained from driving performed by the driver. Smartphone applications are widely used to collect the driving data of the betting. In addition to this, it is also possible to work on the data obtained from the vehicle tracking devices and the in-vehicle sensors which come up with the developing technology. The data handled can be real data or generated on a test platform. In the literature, these data are examined for different purposes, such as driver classification, driver identification, vehicle modeling, and road modeling. In addition, the data discussed also show differences in studies.

Different classification methods were tried by using the attributes extracted from the obtained data. The accuracy percentage of the classification process using the Support Vector Machine, the k-Nearest Neighbor, and the Support Vector Machine-Markov chain method is 98.9,93.3 and 92.2, respectively. The main purpose of the classification of drivers is to provide suitable vehicles to the designated drivers. Each driver will choose the most suitable vehicle for his class and achieve economic and environmental gains.

The main aim of the thesis is to reach exactly this point. The proposed methods are applied to all drivers to achieve improvements worldwide.

2. RELATED WORK

2.1. Driver Classification and Identification

In previous studies, the drivers are usually classified according to the various maneuvers they perform. These maneuvers vary in the studies in the literature, depending on the researcher's handling of the subject. While this maneuver may be a lane change in a study, other studies may be at crossroads or pedestrian crossings. Using real data from smartphones, Junior et al. attempted to identify aggressive driving events from this combination of machine learning algorithms. Various maneuvers have been tested and the best techniques and useful data have been tried to be tested (Júnior Ferreira et al., 2017).

In the study presented by Ehmann and Irmscher (2004), driver errors are modeled by taking into account the drive control parameters and the effect of the driving cycle, thus removing driver types and driving maneuvers. In that study, the drivers were classified into four different classes. Augustynowicz (2009) calculated the aggressiveness of the drivers based on two criteria. Those who change the position of the accelerator pedal most intensively during the test stretches, while their speed varies to the greatest degree. The statistical considerations that are specifically addressed are the standard deviation of the accelerator pedal and speed.

Sathyanarayana et al. (2012) analyzed driver behaviors using the Hidden Markov Method (HMM). Driving with the test vehicle with various sensors installed was carried out and various data were recorded during driving. The driving were completed under different scenarios. The first driving scenario is neutral driving while the second scenario is distracted driving in residential and commercial areas. In the proposed study, 95% accuracy of classification was obtained.

Differences such as age and gender also effect the behavior of drivers in different ways. The Fuzzy-Ruled Based system proposed by Hattori et al. (2011) for driver classification was also used in subsequent studies. Fernandez and Ito (2016) , who deal with this system, thought that they would make the classification better by increasing the rules and parameters. In that study, the drivers are divided into 5 levels (Very Passive, Passive, Normal, Aggressive or Dangerous) considering the frequency of use of acceleration and brake pedals, speed values and driver's ages. However, it turns out that the increasing rules and parameters in the result of the study cannot be helpful in increasing the accuracy. Fung et al. (2017) thought that only the acceleration and deceleration movements were sufficient to classify the drivers and handled elderly people as a working group. As a result of this idea based on the impression that maneuverability decreases with the advancing age, 14 different drives with MultiClass Linear Discriminant Analysis (LDA) classifier have been correctly identified with 90% success. In many studies this has been shown in different forms. The Naive Bayes algorithm, used by Ming et al., achieved 79.4% accuracy with very limited number data. Van Ly et al. (2013) also addressed the braking and turning motion, thinking that only the acceleration and braking movements would not be sufficient to describe the drivers . Support Vector Machine (SVM) and k-mean clustering methods have been investigated by using the feature vectors obtained with these data. A maximum of 65% success was achieved in the study. Besides these two actions, secondary effects and environmental impacts on the driver are also considered to be important factors (Choi et al., 2008).

Zhang et al. (2016) developed a window based support vector machine method and classified the drivers by using the data received by the car and smart phone sensors. The method recommended by using only the data from the telephone classifies with 75.83% accuracy, but this success is 85.83% in the tests using collected data only with car sensors. In the experiments performed with the combination of two sets, the result is 86.67%. Imkamon et al. (2008) used accelerometers, cameras and OBD-II readers to record vehicle speed, engine speed, right-left turn and straight running. In that study, fuzzy logic, is used as the classifier, the results of the questionnaire from three passengers in the test were used to train the system. The passengers categorized the drivers with 3 different levels. While level 1 refers to safe driving, as the level increases, safety decreases and dangerous driving occurs. The average error value was obtained as 0.255.

Castignani et al. (2013) classified drivers into 3 categories: Normal (NOR), Moderate (MOD) or Aggressive (AGG). By using sensors located in the smart phone (accelerometer, magnetometer, gravity sensor and GPS receiver). Smartphone application which can apply Fuzzy Inference scanning is suggested. OBD information has also been added to the mechanism used for classification since the data obtained on smartphones contains noise. In another study that suggested an android application, Meseguer et al. (2013) classified the drivers as Aggressive, Normal, and Quiet. Through this application, speed, acceleration and engine RPM data from collected driver data are used as training data in neural network. As a result of the method proposed in the study, the drivers are separated by 77% accuracy. When the number of classes is reduced, more accurate results can be obtained. But this can be considered as the direction in which the study is lacking. Chen et al. (2015) has identified two classes in the study using the AdaBoost algorithm and reached a high value as a result of classification.

Zheng et al. (2017) examined driver behavior in an environment where pedestrian intensity is high and consequently vehicle-pedestrian relationship is intense. As a result of the study, it is seen that the desired speed and behavior against the spring are important criteria that can be used in driver classification. Aoude et al. (2012) attempted to describe the behavior of drivers at the intersection of roads. Using SVM and Hidden Markov Model (HMM) methods, the drivers are divided into two classes as compliant or violating. The success rate of the study is 85.4% for SVM and 80% for HMM. In his study, Kuge et al. (2000) used the HMM method for driver classification based on lane variation. This study selected lane changing behaviors as driver recognition maneuver. Steering angle, steering angle speed and steering force are used to define the maneuver. In another study, which takes into account the lane change as well as the follow-up distance of the vehicle in front, person behavior was defined using the fuzzy clustering algorithm. Since the driving maneuver was based on longitudinal and lateral acceleration, applied brake pressure, engine speed and some GPS data, these data were recorded as real data (Ma, 2007).

Unlike all these studies, classifications based on the amount of power demanded by the driver are also included in the literature and provide important contributions to energy optimization (Kedar-Dongarkar and Das, 2012).

The data used to classify the drives are fairly large. For this reason, deep learning methods that have attracted attention in recent years have been used in driver recognition and classification studies (Ezzini et al., 2018; Zhang et al., 2018). Ezzini et al. (2018) have worked on the necessity of determining the duration of driver recognition, which they see as a deficiency in previous studies. They suggest that the driver can be identified in 3 minutes using data from two different driving scenarios with 6 drivers participating in the test drive. Instead of using all the data available, simpler models can also be proposed using some of them. Gao et al. (2018) defined periods as stop, wait and go by dividing the rides. In order to define these periods, firstly vehicle speed, longitudinal acceleration, brake pedal position and engine revolutions per minute data were used. In this study, 91.2% accuracy is defined while the simpler model which uses only speed data has 100% accuracy. Taking into account other factors in traffic (neighboring drivers, pedestrians and cyclists), the study takes into consideration that the first step is to classify the drivers to provide a safer navigation device to the drivers (Cheung et al., 2018).

By classifying the drivers in different ways, solutions to different problems can be produced. Therefore, different class labels are used for different purposes. In the study proposed by Bernardi et al. (2018), when different scenarios and different labels were examined, the highest classification accuracy (0.97) was obtained by gender. One of the problems is fuel consumption. One of the most important problems that should be taken into consideration when the problems of the world's energy resources decrease and ecological balance are considered is fuel consumption. Ping et al. (2019) classify drivers into three groups by using unsupervised machine learning method of spectral clustering. Six driving behavior-based fuel consumption features are have been obtained from real driving data. Different from previous work, only drivers are changed due to the inability to determine which factor caused the change.

2.2. Optimization of Electric Vehicles

In the thesis presented by Vaz (2015) regarding the energy method, which is considered as one of the most important issues related to electric vehicles, the driver adopts the driving strategy in accordance with the stored battery energy. First, the driver is informed about the current driving situation, while the driver is guided to choose between the optimal trip speed and the optimal acceleration strategy. Fleet-style electric bus was used as a test tool. By choosing the right driving strategy, energy consumption is reduced from about 1 kWh/mile to 0.6-0.7 kWh/mile. The 13.9% increase in trip time due to driving strategy is accompanied by a decrease of 5.6% in the amount of energy consumed when driving in the designated test area. The advantages of the proposed strategy include a significant increase in driving time versus a significant reduction in energy consumption, allowing flexibility in the choice of driving parameters and implementation without significant changes in existing EV designs.

The demanded power in electric vehicles is the most important parameter to consider when working with energy management. Energy management is very sensitive to this power value. With the development of computational and sensing techniques/applications, it is possible to estimate the internal load for the optimization of energy management. In order to increase the applicability and development of the studies on electrical tools, it is necessary to work with real data rather than virtual data. Therefore, real data such as driving behavior and frequency of use should be included in the studies, including energy management and range increase studies. Opila et al. (2013) designed the shortest path controllers based on stochastic dynamic programming, taking into account the constraints on fuel economy and powertrain activity, and this design was also simulated on the vehicle model developed by them. The Volvo S-80 prototype, used as a test track, has focused on three key issues to achieve functional control. The first is to get a real-time application that runs within the calculations and memory information. The second issue is the ability to react quickly to pedal change, while the shifting and engine starting commands are the third. The controller was performed in the on-loop hardware system before it was tested in the vehicle. The acceleration value equal to a driving cycle is modeled as a fixed finite state markov chain in the energy management problem. The controller minimizes the cost function that reflects fuel consumption and the use of power systems. The driving cycles used in the test phase are the general cycles previously defined. However, this model can be created with real driving data. In the present study, a method was proposed and tested to improve the response speed of the drivers to shifts. The application works in relation to actuator delays and impossible operating points.

In some studies related to energy management of electric vehicles, it has been revealed that driving conditions should be taken into consideration besides system and mechanical parts. Driving style, driver's driving characteristics and traffic situation directly affect the charging time of the electric car. How the maneuvers during driving affect the energy requirements has been demonstrated by experiments. Therefore, even giving the driver only the optimum speed to use the vehicle reduces the amount of fuel consumed during travel. To save fuel, a driving style called Eco driving is defined. The necessary warnings are given to the driver considering the traffic and road conditions and the speed information to be used is given. In this way, the driver tries to avoid sudden maneuvering and acceleration movements.

Economic driving strategies provide drivers with a specific driving framework, saving approximately 15% and 25% of fuel for that trip, but it is difficult to comply with the rules as the driving behavior is personal (Hiraoka et al., 2009; Taniguchi, 2008). In this study, tests were performed to reveal the positive contribution to fuel consumption by changing the average speed. Cerbe et al. (2009) used two different roads for driving with three different average speeds. When traveling time and fuel consumption are evaluated for different average speeds, it is observed that the increase in travel times by 7.8%, 6.25% and 7.5%, while the decrease in fuel consumption by 27.6%, 10.8% and 10.9% is observed. . They found that these values did not change for different roads, that the change occurred due to factors such as travel distance, maximum allowed speed and digital map of the road. There are also devices that provide instant speed information according to arrival time without considering fuel consumption (Giszczak, 2006). In the study of driving style classification, it has been shown that a journey at low speeds is not complete with a higher average speed but causes more carbon emissions (Rhys-Tyler and Bell, 2009).

In order to optimize energy consumption, environmental factors need to be considered. Jiménez et al. (2014) has taken into account the road and traffic information. The aim of the study is to create a speed profile that will reach the target within the specified time with minimum fuel consumption. Dynamic Programming (DP) method was used as optimization method. When selecting the appropriate value for the DP speed shift, the path takes into account such information as vertical profile, speed limit and timing. The amount of fuel consumed and travel time is related to speed shift.

Styler and Nourbakhsh (2015) used the Global Positioning System (GPS) coordinates, speed and power load data in their optimization approach for energy management. This data is taken from the vehicle computer and external sensors. While speed, acceleration and power demand information is obtained from the sensors of the vehicle, information such as GPS and time are taken from outside. Data is assembled for both electric and gasoline vehicles. Temperature, charge status, instant load information are also needed. Defining the system structure and characteristics is a requirement for the control algorithm. By supplying the state property vector, the demanded power is estimated using dynamic programming. The effect of this prediction route, topology information, driver behavior and traffic information on power makes it difficult to analytically calculate this prediction. The algorithm evaluates the previous load information as a prediction. The state vector is compared with the previous state vectors and presented as a state estimated load following similar states. In case of more than one projection, it is desirable to establish a control strategy that targets the least cost. The tests were conducted with electric vehicles with data from real drivers. These data are daily vehicle usage data of real drivers from eight different vehicles for 10 months. The proposed algorithm has succeeded in reducing energy consumption by 10%.

Vrodey et al. (2013) used two-year vehicle data of five Peugeot iOn vehicles as the data set. The vehicles were used as personal vehicles, service vehicles and rental vehicles. Based on these two-year data, averaged energy balance Sankey diagram of the cars was created. Different energy models have been observed depending on different driving patterns, travel types/profiles and frequency of driving. While some vehicles were used for the same purpose during the test period, changes were made for some vehicles. Therefore, different consumption profiles were observed for all vehicles.

The basic mechanical, electrical and power electronics components must be used in optimum dimensions so that the hybrid electric vehicle (HEV), which combines the elements of the electric drives and the internal combustion engines, has an appropriate transportation design. Weinstock et al. (1993), the vehicle battery, auxiliary power unit, traction motor, variable frequency traction drive is defined as the basic components of the hybrid electric car. If it is aimed to reduce gas emission, the battery capacity should be regulated first. Because the main determinant of the emission range is the battery. The battery size cannot be continuously increased because it directly increases the mass and volume of hybrid the electric vehicle. Battery capacity can be maximized by observing the limits. The auxiliary power unit (APU), consisting of an internal combustion engine (ICE), an induction generator, and Pulse Width Modulation (PWM) inverter control, will automatically enter the system when the battery pack drops to 30% of the rated capacity. When selecting the electric vehicle engine, the engine traction system must be considered. The most important performance criterion expected from this engine is high torque and low mass. Consequently, high efficiency can be achieved.

Fellini et al. (1999) provides alternative engines with features such as modularity, allowing the introduction of new components into the system, and the flexibility to use different and existing codes. For this, a simple application with MATLAB and CORBA is included in the hybrid diesel electric power system.

Hybrid electric vehicles, including hydrogen powered fuel cells, are becoming more widespread in addition to gasoline fuel plug-in hybrid electric vehicles due to their clean and efficient power generation. Jain et al. (2009) studied the sizing of energy storage components for the fuel cell plug-in hybrid electric vehicle (FC-PHEV). Ni-MH battery was used as the second energy storage component in the vehicle. Such a PHEV structure is used for charging grid batteries and for electrolysis of water. Thus, this structure provides an additional degree of freedom to produce hydrogen and oxygen, which increases the drivetrain efficiency while at the same time increasing the driving range of the vehicle. Due to this freedom, they have more efficient and high performance power transmission requirements than ordinary PHEV or FC-HEVs. In this study, while multi-purpose genetic algorithm is utilized for size optimization of power transmission systems, Liu et al. (2007) developed an adaptive hybrid genetic algorithm to solve this problem. The findings of the study showed the validity of the method developed for optimum sizing and the effectiveness of the hybrid genetic algorithm. Based on these results, improvement suggestions were made for the vehicle used. The proposed algorithm uses adaptive crossover and mutation possibilities to ensure the diversity of the population taking into account the generation effect and individual differences. A better global convergence is aimed by reverse crossing and mutation processes. A hybrid algorithm with better convergence rate was obtained by combining the Local Search method (Sequential second order programming (SQP)).

Hegazy and Mierlo (2010) propose a design that minimizes the cost, mass and volume of these components, taking into account the need to meet certain design and control requirements in the dyeing of fuel cell (FC) and supercapacitor (SC) in fuel cell hybrid electric vehicles. Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) has been tried to design the power transmission system by using two different optimization methods. The simulation results of MATLAB/SIMULINK have shown that the dimensioning of power transmission components has been improved by the PSO method, which has resulted in high operating performance in fuel cell hybrid electric vehicles. FCHEV was analyzed in two different driving cycles: Federal Test Procedure (FTP75) Urban and New European Driving Cycle (NEDC). For the specified driving cycle, the optimum number of units is determined for all components, respectively, while minimizing the size and cost of the fuel cell and the supercapacitor. According to the study, compared to a hybrid electric vehicle with a supercapacitorless fuel cell, the vehicle considered increased by 9.22% in NEDC and 13.29% in FTP75. In addition, the total cost reduction of fuel cell and supercapacitor components is around 13.40% in NEDC and 12.21% in FTP75. As a result of the experiments, it is concluded that PSO method is more useful than GA method for the optimization of such a tool.

Tara et al. (2010) studied the issue of optimum sizing in order to obtain plug-in hybrid electric vehicles by adding additional energy storage components to the hybrid electric vehicle. They proposed a simulation-based framework for sizing. Simulations were performed using a midsize sedan (Toyota Prius) with average parking times used for personal transport. Data were obtained from driving in the city of Winnipeg (Canada). There are restrictions on battery sizes for low pricing. In view of these limitations, there are three different battery technologies commonly used in simulations for battery sizing. Vehicle dynamics, vehicle controller, regenerative braking, battery, model parameters were taken into consideration during the simulations. The Nickel Metal Hybrid (NiMH) battery technology offers more possibilities for expansion for medium-weight and cost-effective relatively small-volume vehicles. It has also been shown that the Lithium-ion (Li-ion) chemistry needs to be developed in order to achieve lower costs. With the study, it is possible to charge the electric vehicles both at night and at least three hours of parking.

Schaltz et al. (2009), battery and ultrapapacitor were compared in their studies on the rating depending on the system volume, system mass and battery life. When dimensioning energy storage devices, not only power and energy requirements, but also battery life must be taken into account. In the energy management strategies presented in the study, the load cell is appropriately divided among the fuel cell, battery and ultracapacitors. There is also a charging strategy that installs energy storage devices taking into account the FCHEV requirements. Analyzes were performed for FCHEV with the data obtained from the test driving cycle lasting more than three weeks. In addition to the two energy management strategies and charging strategy for energy storage devices presented for FCHEV, recommendations were also made on propulsion and power system configuration and sizing. In the first of these two energy management strategies, the ultracapacitor, one of the energy storage devices, operates as a high-pass filter for load power. In another strategy, the ultracapacitor is used as an energy source to increase battery life.

In order to investigate the effect of driving style on CO2 emissions, an analytical method based on eco-driving rules was developed by means of the data obtained from the vehicle developed by the Transport and Logistics Center (CTL) at Sapienza University of Rome. The United States Environmental Protection Agency (EPA) reported in 2012 that the traffic is responsible for 30% of CO2 emissions. The study states that the amount of gas released will be reduced by changing the use of personal vehicles (Barkenbus, 2010). There are a few steps the driver can take to achieve this goal. Preferring less fuel consuming vehicles, using low carbon emission vehicles, using their own vehicles more efficiently and using public transportation instead of individual vehicles are some of the simple measures that can be taken. When the data obtained from the driving tests were examined, it was seen that even the lower average speed, economical driving style results in less fuel and less gas emissions. Moreover, this decline is even lower when it comes to higher average speeds. For a gasoline vehicle with an average speed of 10 km/h, this reduction is approximately 30% and 22% for a 40 km/h diesel fuel vehicle. However, in the case of an average speed of 80-90 km/h, the effect of driver behavior on fuel consumption can be ignored, and the aforementioned decreases can be ignored. This is because improvements in fuel consumption and CO2 emissions are more common at low average speeds and disappear with rising average velocities. Therefore, eco-driving behavior can be defined as a function that varies depending on the average speed value and makes a more intensive difference in speeds at which driving behavior is more effective. In a situation where drivers, such as personal transport, have direct influence on transport, eco-driving changes the CO2 emissions by 32% to 41% (Bin and Dowlatabadi, 2005; Vandenbergh, 2005; Vandenbergh and Steinemann 2007).

Messagie et al. (2014) compared the environmental performance of various vehicle technologies and considered the gas emissions and end-of-life processes of vehicle parts during the production phase. In the work, electric vehicles (BEV), fuel cell electric (FCEV) and fuel vehicles (petroleum, diesel, compressed natural gas (CNG), liquefied petroleum gas (LPG), bio-diesel and bio- ethanol) were used. The aim of the study is to determine the environmental impacts of the vehicles and to develop a model that will enable the all life cycle (LCA) of the vehicles to be defined more accurately. In this study, results such as climate change, respiratory effects, acidification and mineral extraction damage are presented for various vehicle technologies.

Karabasoglu and Michalek (2013) compared vehicle life and greenhouse gas emissions in driving scenarios such as New York City (NYC), highway test conditions (HWFET), and various driving conditions (such as frequent stop-start and aggressive use). In this study, three different vehicles were examined: hybrid, extended-range plug-in hybrid and battery electric vehicles. It has been shown in the study that in different types of vehicles for different driving types, there are positive reductions in fuel consumption and gas emissions. For the NYC driving cycle, hybrid and plug-in vehicles have reduced gas emissions by 60% compared to conventional (CVs) vehicles, while cost has decreased by 20%. In the driving cycle of the highway test conditions, in contrast to the previous one, there is a significant reduction in both meltdown and gas emissions in electric vehicles. In addition to the differences arising from the vehicles used, there are differences in the way the vehicle is driven in the same vehicle and in the same driving cycle. In frequent NYC conditions, gas emissions of traditional vehicles tripled and cost increased by 30%, while aggressive driving decreased by 45% for all-electric range of plug-in vehicles compared to lighter test cycles. Studies carried out in test environments in which drivers' behavior and driving cycles are not taken into account are incomplete. As a result of this study, it has been shown that with the increase of hybrit and plug-in vehicles, the determination and use of the vehicle suitable for the driver gains more importance. For a driver traveling in NYC conditions, choosing a hybrid vehicle instead of traditional vehicles means 20% cost savings and 60% less GhGs emissions. In addition, a vehicle used in the HWFET driving cycle offers a cheaper ride despite the high emissions of GhGs.

Vehicle performance is generally determined by taking into account the acceleration time when reaching the specified speed from 0. In addition, the maximum speed and torque that the vehicle can reach is also important.

3. DRIVER CLASSIFICATION

3.1. Driving Data

The driving route where the rides will be carried out has been tried to be selected in such a way as to meet all conditions encountered in real life. Therefore, instead of an artificial simulation environment, a specific region within Afyon Kocatepe University was chosen. Within this 2.2 km long track, there are traffic elements such as pedestrian crossing, bumps, pits, intersections, u-turn, secondary roads. Therefore, almost all possibilities to be encountered on a random path at any time on any given day are taken into account in the experiments. These experiments were carried out during the hours of pedestrian flow, and the pedestrian, which is one of the living elements of the traffic, created the effect it should have in the data base. There are also vehicles on the road in question, except for the test vehicle. This means the inclusion of other vehicle drivers, the other living element. The driving route is shown in figure 3.1.

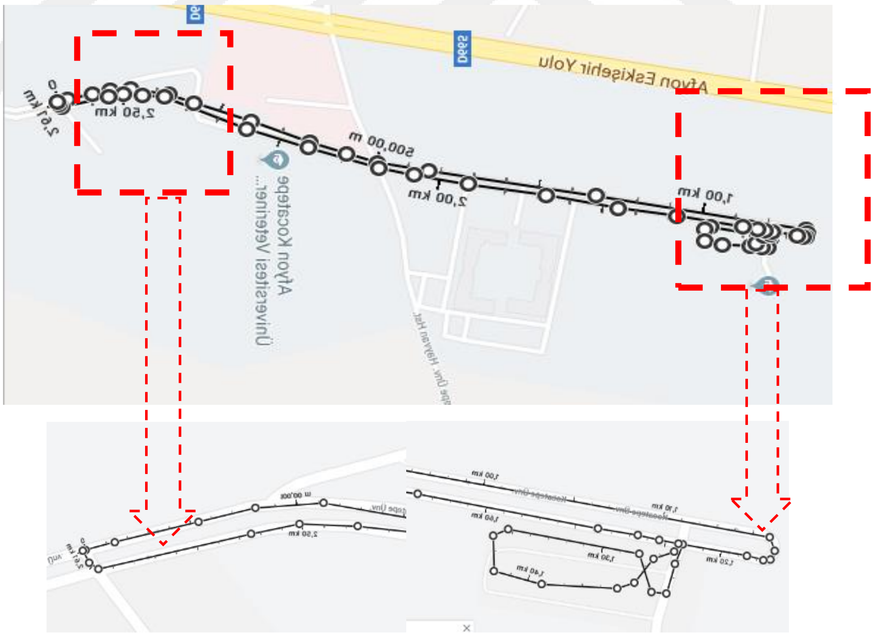


Figure 3.1. *The driving route (2018 Google ©-Map Data)*

Drivers are academicians of different age and gender selected from university staff. The age range of the drivers varied between 28-40 during the experiment. The age distribution of male and female drivers was tried to be equal. Four female and nine male drivers participated in the study and all riders had an average of 3 rides. No information is given to drivers before the road. All rides were carried out under the same driving conditions. 2015 Toyota Corolla vehicles were used for test drives. The vehicle was selected as an automatic gearbox since it was thought that due to the habits of the automatic gearshifts of the test participants, the change of gear could be changed on the accuracy of the data to be obtained. The test vehicle is capable of high speeds and sudden acceleration. It has been ensured that the test vehicle is strong and comfortable enough to meet the demands of all classes. Considering the psychological studies of the drivers, the driver's knowledge that he/she was subjected to a test drive was deemed to change the driving behavior and the drivers were not informed about how to evaluate the result of this ride. The fact that drivers were not informed of the recorded data made them fully reflect their own behavior. In addition to the drivers, the observer participated in all the rides. As a result of the rides, the observer was asked to classify the drivers. The observer was selected as a person who has mastered the scientific literature on driver behavior. The vehicle tracking device and the smartphone application placed in the test vehicle recorded data simultaneously. By recording data with two separate devices, both loss of data is prevented and the negative effect of disturbing effects such as noise is eliminated. This also proves that the data is recorded correctly. Data were recorded at frequencies of 1 Hz and 100 Hz. The frequency value varies according to the data type. Many data such as time, latitude, longitude, altitude, speed, 3D acceleration, 3D angular velocity, horizontal and vertical accuracy were recorded. The data selected are listed in Table 3.1.

Table 3.1. *Driving data*

Signal name	Symbol	Units
Longitudinal Acceleration	a_y	m/s^2
Lateral Acceleration	a_x	m/s^2
Vertical Acceleration	a_z	m/s^2
Speed	v	km/h
Longitudinal Angular Velocity	w_y	rad/s^2
Lateral Angular Velocity	w_x	rad/s^2
Vertical Angular Velocity	w_z	rad/s^2

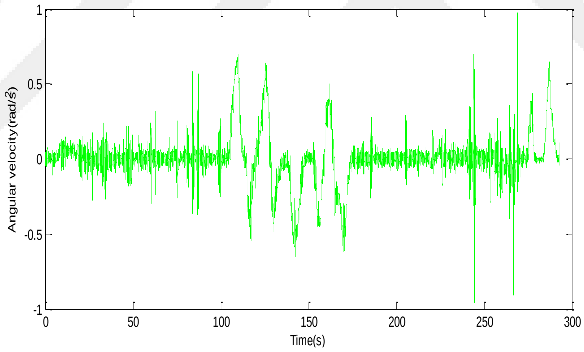
3.2. Feature Extraction

Once the studies in the literature are examined, it is stated that the acceleration rate and speed are sufficient when the persons are distinguished. However in this more detailed study, it has been shown that angular velocity in addition to this data is the decisive factor in driver classification. Using the obtained data, 4 different features were revealed. It has been found that these features are sufficient for defining the driver group of the persons.

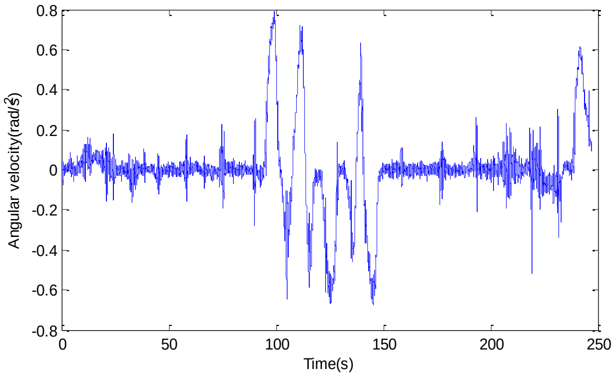
Feature 1: The angle of rotation and speed are used to identify rotational events and differentiate them in driving. Therefore, the feature vector defined for rotation events is generated by taking angular velocity into consideration. As seen in Eq.(3.1), the angular velocity value is inversely proportional to the half-circle of the axis of rotation, which is linear with the velocity of the vehicle.

$$\boldsymbol{\omega} = \frac{\boldsymbol{v}}{\boldsymbol{r}} \tag{3.1}$$

In Eq. (3.1) v and r denote the speed of the vehicle and radius of the curve, respectively. The rate of increase of the angular velocity value defines how sharp and fast the rotational motion is made. In figure. 3.2, angular velocity values of drivers are shown.

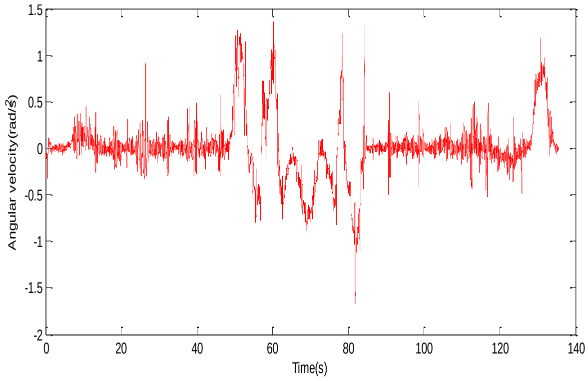


(a)



(b)

Figure 3.2. Angular velocity values of drivers (a-conservative, b-moderate, c-aggressive)



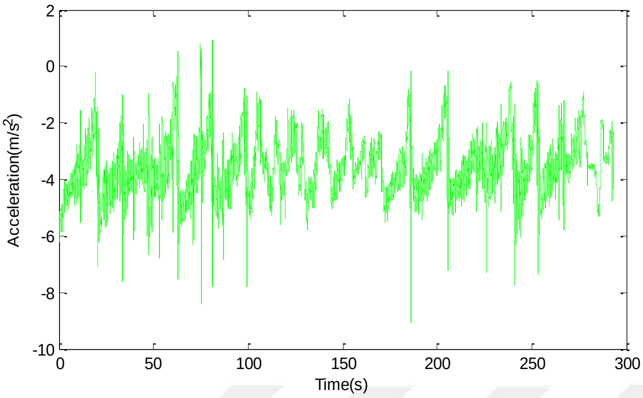
(c)

Figure 3.2. (Continue) *Angular velocity values of drivers (a-conservative, b-moderate, c-aggressive)*

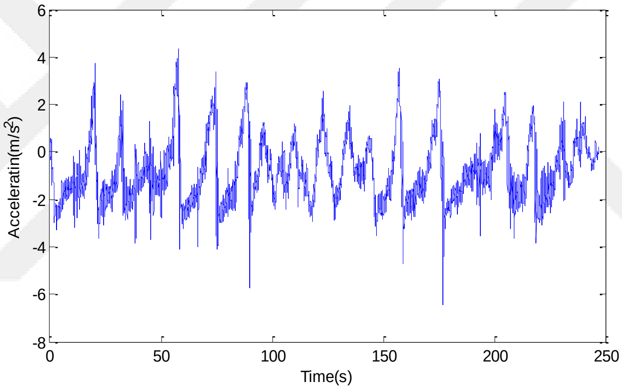
In these figures, positive and negative angular speeds indicate that the vehicle is turning to the right or to the left. The angular velocity of the first driver is about 0.5 rad/s^2 while the angular velocity of the third driver is about 1.5 rad/s^2. In addition, the time during which the rotation was performed also varied due to the difference in speed values. Angular velocity data do not provide very meaningful results in direct discrimination of drivers. For this reason, the angular velocity values obtained during driving are taken as norms and feature 1 is defined as Eq. (3.2).

$$w_n = \sum_{i=1}^{N} \left| w_{z_i} \right| \tag{3.2}$$

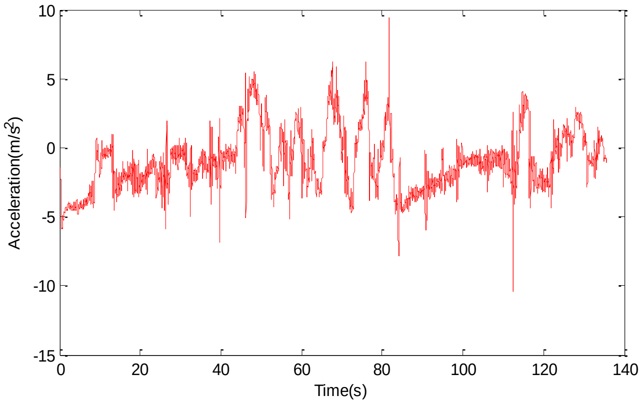
Feature 2: The acceleration and deceleration of the vehicle is the repetitive actions taken by the driver during a journey and how these two processes differ according to the person. For instance, a driver may prefer constant braking to adapt to faster driving; however, another driver may move slower and apply the brakes gradually. Therefore, the answers of these questions are searched: the driver used the gas and brake pedals at what frequency? At which values? Acceleration and braking operations are related to the longitudinal acceleration data in the dataset. Changes in the acceleration values of the drivers in different classes and the frequencies of the changes are clearly observed when the graphs given in Figure 3.3 are examined.



(a)



(b)



(c)

Figure 3.3. *Longitudinal acceleration values of drivers (a-conservative, b-moderate, c-aggressive)*

The feature value is obtained by Eq. (3.3).

$$a_n = \sum_{i=1}^{N} \left| a_{y_i} \right| \tag{3.3}$$

where a_y is longitudinal acceleration.

Feature 3: Previous studies have shown that different dynamic properties of different vehicles are related to the vertical acceleration and angular velocity of the vehicle during transition from bumps as the vehicle travels at a certain speed. In this study, differences arising from driving on the same route with the same vehicle are interpreted as the reaction of the drivers to the road conditions. The acceleration data is taken as a result of the correlation of the horizontal acceleration with the angular velocity. Experiments that are not performed at a specific speed also require the longitudinal contribution to account. As a result, a feature within three-axis acceleration is occurred. With feature, given in Eq. (3.4), specified as the area under the 3-axis acceleration, the reaction of the driver against the obstacle and the hump on the road has been revealed.

$$a_t = \sqrt{{a_x}^2 + {a_y}^2 + {a_z}^2}$$

$$A = \int_0^t a_t \, dt \tag{3.4}$$

. The driving matrix obtained from 39 driving is given in Table 3.2.

Table 3.2. *Data matrice of driving*

Feature No Driving No	Feature 1	Feature 2	Feature 3
1st Driving	27383.8210	8343.1882	2871.5854
2nd Driving	27126.4369	8052.3325	2821.4269
3th Driving	27245.2549	8700.1209	2816.3529
4th Driving	27632.5107	9006.7038	2887.8901
5th Driving	21922.0777	3528.3831	2913.4751
6th Driving	21533.6939	3673.2568	2733.1964
7th Driving	24011.1406	3910.1762	3076.6017
8th Driving	22045.7049	3607.8123	2823.3450
9th Driving	30031.6753	9909.2231	3339.2539
10th Driving	29329.2045	9697.6460	2913.3727
11th Driving	27296.8188	9974.7528	2743.9896
12th Driving	26713.3265	10296.2812	2629.5596
13th Driving	29557.7359	4214.2626	2836.4263
14th Driving	26907.7533	4882.16188	3088.4964
15th Driving	22418.4302	9073.7968	2659.2370
16th Driving	23088.1991	8896.58695	2492.3080
17th Driving	27107.3366	10933.0381	2816.0600
18th Driving	26588.6761	10504.6090	2595.4167
19th Driving	16713.9712	6463.0758	2674.8207
20th Driving	15077.2604	5569.4462	2766.3078
21th Driving	36321.6208	5112.4039	3036.0650
22th Driving	28606.5300	4363.0709	2658.9879
23th Driving	24642.5759	2963.1430	2293.2266
24th Driving	24124.2186	2849.2136	2351.0778
25th Driving	23791.1277	3542.0785	2403.3884
26th Driving	24079.6289	3265.2184	2411.6683
27th Driving	23212.5083	3094.4938	2369.7311
28th Driving	23095.2506	2822.4979	2473.4978
29th Driving	25118.0058	5497.2100	2812.3014
30th Driving	27827.2088	10474.7006	2687.9523
31th Driving	28486.2995	10555.7210	2703.8158
32th Driving	27672.9616	5190.6188	2752.4948
33th Driving	26584.8706	5448.8068	2680.6193
34th Driving	22492.5655	4938.2072	2694.4651
35th Driving	22912.3017	4720.6937	2738.7521
36th Driving	23437.3648	4826.9385	2645.9003
37th Driving	22909.7596	4714.3612	2660.5308
38th Driving	15699.4372	2627.4373	2572.9282
39th Driving	13720.8914	2663.6334	2583.0852

Without any proposed feature vectors, there is no direct deduction for the class of drivers to which the drivers belong. Moreover, it does not make any sense that these data are directly applied to the mentioned algorithm. Figure. 3.4 shows speed information of 9 different drivers belonging to 3 different groups.

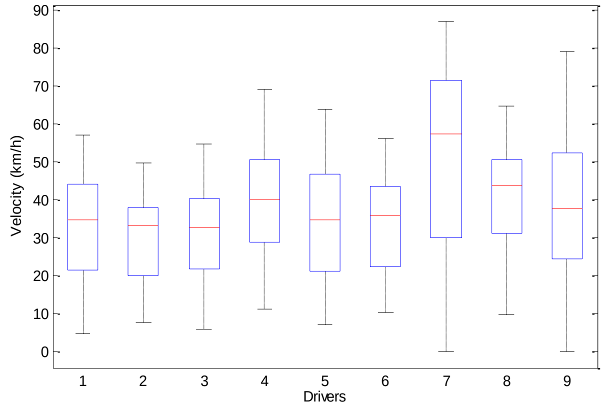


Figure 3.4. *Velocity (speed) frequency diagram of drivers (1-2-3: conservative, 4-5-6: moderate, 7-8-9: aggressive drivers)*

It is seen when the figure is examined that, the speed values of different drivers which are not in the same group can show similarity. The maximum speed values of a driver in a normal and aggressive class may be equal, while a driver in a quiet group and a driver in a normal group may have equal minimum speed values. This shows that, the right data must be handled correctly in order to distinguish the drivers. While equal values can arise, the frequency and range of these values vary for the drivers.

An aggressive driver turns the same turn at faster speeds and/or narrower angles, while a conservative driver rotates at a lower and/or wider angle. Figure 3.5 shows the angular speed information of 9 different drivers.

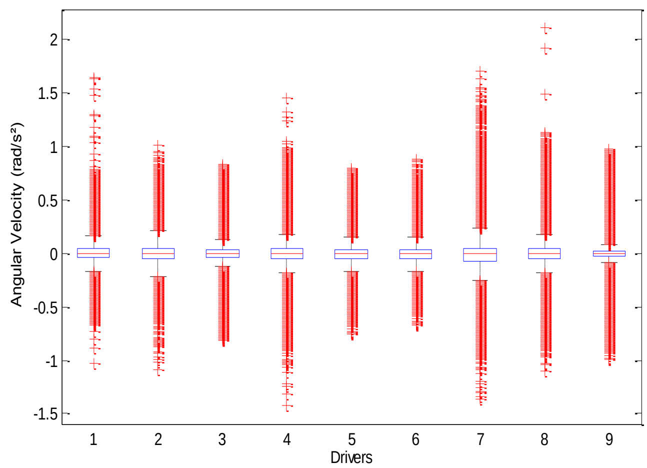


Figure 3.5. *Angular velocity frequency diagram of drivers (1-2-3: conservative, 4-5-6: moderate, 7-8-9: aggressive drivers)*

The angular speed change interval increases as the driver moves from the quiet driver to the aggressive driver. This interval can be used as a criterion in the classification by taking the norm angular velocity. Considering 3 different features from the recommended features, driver identification can be performed but the driver is not able to be classified. Fig 3.6 shows the drivers identification using features. All the data needed for classification with the use of all features are included in the algorithm.

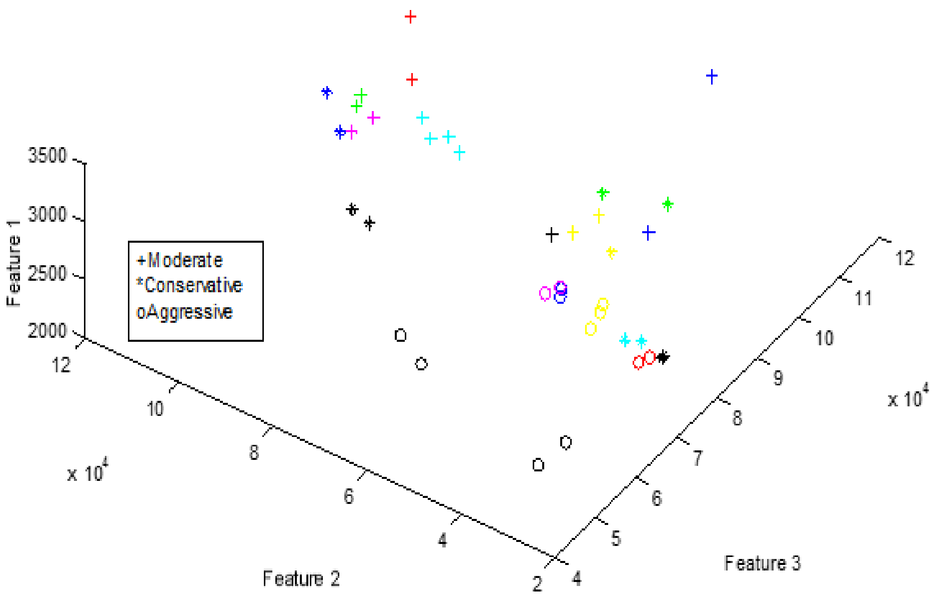


Figure 3.6. *Driver identification with the features*

3.3. Classification Methods

In this thesis, drivers were classified using different methods (Support Vector Machine Method, Markov Method, Hybrid Markov-Support Vector Machine Method and K-Nearest Neighbor Method). In this section, the methods used in the thesis are explained respectively and the results obtained by applying these methods to the thesis data set are given.

3.3.1. Support vector machine

Support Vector Machines (SVM) is a supervised classification technique based on statistical learning theory and its foundations were developed by Cortes and Vapnik (1995). SVM is a machine learning algorithm that tries to generalize and estimate new data by learning on training datasets without assuming any information about its distribution. Input variables and outputs in training sets are mapped. By means of data pairs, the decision functions that separate data from different classes are obtained (http-1). New data input variables are classified with the decision function. In general, the operating principle of SVM is the determination of the decision boundaries (hyperplanes) that optimally separate the data from the two classes (Vapnik, 2000). The most basic classification problem for SVM is the classification of a two-class data set that can be linearly separated. In order to solve this problem, SVM tries to determine the best separator plane which makes the distinction between the two classes the best and the boundary between the classes is maximum. The best separator plane maximizes the distances of the data for each class from the separator plane. Training data closest to hyperplanes form support vectors that define the boundary between the two classes (http-1).

Support Vector Machines are basically divided into two according to the linearity and non-linearity of the data set.

3.3.1.1. Linear support vector machine

The data used in the linear support vector machine method differ depending on whether or not it can be separated linearly.

Linear support vector machine for linearly separated data

Support Vector Machines is a two-class classification technique and it is aimed to classify the test data of the two classes with the objective function ($g(x) = sign(f(x))$) obtained from the training data in the classification operations using SVM. These two classes are usually represented by (-1, +1) class labels. When the input data can be separated linearly, it aims to select the separator plane from the infinite number of separator planes that will make the decision limit the largest. The objective function, which will classify the test data, is determined using the best separator plane obtained from the training.

$x \in R^N$ feature vectors for the data in the training set, $y_i \in \{-1, +1\}$ label is to show the class; a plurality of separating planes can be plotted to distinguish between positive and negative labeled data. The purpose of SVM is to find the separating plane that maximizes the distance between the nearest points to it. This separator plane is best called the separator plane and the points adjacent to this plane that limit the boundary width are called support vectors. This provides any x_i point Eq. (3.5) on the separating plane. Where w represents the normal vector of the separating plane and b represents the orientation value.

$$(w \cdot x_i) + b = 0 \tag{3.5}$$

$E = \{x_i, y_i\}, i = 1,2, \dots, N$, is accepted as an N-element data to be used for SVM training. Inequalities of the best decision limit are written as Eq. (3.6) and Eq. (3.7).

$$(w \cdot x_i) + b \geq +1, for\ y_i = +1 \tag{3.6}$$

$$(w \cdot x_i) + b \leq -1, for\ y_i = -1 \tag{3.7}$$

An infinite number of lines can be drawn to divide a two-class data set. The objective will be to minimize the classification error when an unknown data set is encountered; to select the line that maximizes the distance between samples of different classes. Because the decision limit, which is as far away from both class data as possible, is the best separator. The large limit ensures that the estimation is reliable in the training set and that the prediction performance on new samples is good. Appropriate w and b values should be calculated to find the best separator plane.

The Eq. (3.6) and (3.7) of the boundary hyperplanes expressed by the distance from the origin are calculated as $\frac{|1-b|}{\|w\|}$ and $\frac{|-1-b|}{\|w\|}$ respectively. The distance between these two hyperplanes is $\frac{2}{\|w\|}$. While the best separation plane is found, the distance of this plane to the border is tried to be maximized. For this, the expression $\|w\|$ should be minimized. In this case, the $min\left[\frac{1}{2}\|w\|^2\right]$ expression must be calculated based on the condition Eq. (3.8) to find the maximum limit.

$$y_i\big((w \cdot x_i) + b\big) - 1 \geq 0, y_i \in \{-1, +1\} \tag{3.8}$$

This problem is a nonlinear constraint optimization problem expressed by condition and equation. This optimization problem can be solved by using Lagrange function and Lagrange multipliers $(a_i, i = 1, \dots, N)$. a_i values are Lagrange multipliers (Kavzoğlu and Çölkesen, 2010, http-2). The Lagrange equation in Eq. (3.9) is minimized according to the variables w and b, and is maximized according to the multipliers a_i.

$$L_p = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{N} a_i\big[y_i\big((w \cdot x_i) + b\big) - 1\big] \tag{3.9}$$

The problem is written as Eq. (3.10) and optimization problems can be converted to secondary forms.

$$\underset{a}{argmax}\ \underset{w,b}{\min}\left[L_p\right] \tag{3.10}$$

Lagrange equation is solved by taking partial derivatives according to the correct variables and the results are placed in the Lagrange equation and eliminated. The result is a correlation that will be greatest only in Lagrange multipliers (Vapnik, 2000).

From the partial derivatives of primary Lagrange equation according to w and b, Eq. (3.11), (3.12) and (3.13) are obtained (http-2).

$$\frac{dL_p}{dw} = 0 \Rightarrow w = \sum_{i=1}^{N} a_i y_i x_i = 0 \tag{3.11}$$

$$\frac{dL_p}{db} = 0 \Rightarrow w = \sum_{i=1}^{N} a_i y_i = 0 \tag{3.12}$$

$$L_d = \sum_{i=1}^{N} a_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} a_i a_j\, y_i y_j x_i^T x_j, a_i \geq 0, \forall i \tag{3.13}$$

Eq. (3.13) is a quadratic programming (QP) problem and this complex problem is obtained as equality Eq. (3.14) using the Karush-Kuhn-Tucker (KKT) complement condition (http-2).

$$a_i\big(y_i\big((w \cdot x_i) + b\big) - 1\big), i = 1, \dots., N \tag{3.14}$$

Eq. (3.10) is solved and b value is obtained as Eq. (3.15).

$$b_i = y_i - w \cdot x_i \tag{3.15}$$

There is one Lagrange multiplier for each sample in the training set. During the solution of the equation obtained with positive-valued Lagrange multipliers x-vectors aval of support vectors, these support vectors are located on the hyperplanes that provide the Eq. (3.14). When the objective function defined by Eq. (3.16) is recalculated using calculated x_i support vectors, a_i weight multipliers and Eq. (3.11), equality becomes Eq. (3.17).

$$f(x) = sign\big((w \cdot x_i) + b\big) \tag{3.16}$$

$$f(x) = sign(\sum_{i=1}^{N} a_i y_i (x \cdot x_i) + b) \tag{3.17}$$

Eq. (3.17) is calculated to test a new data *x*, and if this total is positive, *x* is called first class, otherwise *x* belongs to second class.

Nonlinear support vector machine for linearly separated data

In many classification applications, it is not possible to separate data sets linearly. This problem is solved by defining an error variable because some of the training data remains on the other side of the best separator plane. In order to calculate the best separator plane, the inequalities Eq. (3.6) and (3.7) are rewritten together with the value of training error deviation Eq. (3.18), Eq. (3.19) and Eq. (3.20) inequalities.

$$(w \cdot x_i) + b \geq 1 - \zeta_i, for\ y_i = +1 \tag{3.18}$$

$$(w \cdot x_i) + b \leq -1 - \zeta_i, for\ y_i = -1 \tag{3.19}$$

$$\zeta_i \geq 0, \forall_i \tag{3.20}$$

Using the above equations, Eq. (3.21) can be created.

$$y_i\big((w \cdot x_i) + b\big) - 1 + \zeta_i \geq 0, y_i \in \{-1, +1\}\ and\ \zeta_i \geq 0 \tag{3.21}$$

In this case, for the x_i data to be incorrectly classified, $\zeta_i < 0$. The fact that a correctly classified *x* data set is between $0 < \zeta_i < 1$ means that this data is actually located between two boundary hyperplanes.

The best generalized separation plane is determined by the vector w minimizing the function $\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\zeta_i$. In this case, the expression $min\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\zeta_i$ must be calculated on the condition Eq. (3.18) to obtain the maximum limit (Vapnik, 2000). Here is the tradeoff parameter between the error and the boundary. The optimization problem is as in Eq. (3.22).

$$min\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\zeta_i \text{subject to } y_i\big((w \cdot x_i) + b\big) - 1 + \zeta_i \geq 0, y_i \in \{-1, +1\} \tag{3.22}$$

The upper limit C allows Lagrange multipliers to remain between $0 < \zeta_i < 1$ (Vapnik, 2000). A nonlinear constrained optimization problem expressed by this condition and equation can be solved by using the Lagrange function and Lagrange multipliers $(a_i, i = 1, \dots., N)$. a_i values are Lagrange multipliers (Kavzoğlu and Çölkesen, 2010; http-2).

The Lagrange equation given in Eq. (3.23) is minimized according to the variables w, b and ζ_i, and is maximized according to the multipliers a_i.

$$L_p = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\zeta_i - \sum_{i=1}^{N}a_i\big[y_i\big((w \cdot x_i) + b\big) - 1 + \zeta_i\big] - \sum_{i=1}^{N}\mu_i\zeta_i \tag{3.23}$$

The μ_i value in this expression is the Lagrange parameter, which makes the ζ_i value positive. The problem is written as Eq. (3.24).

$$\underset{a}{argmax} \ \underset{w,b}{\min}[L_p] \tag{3.24}$$

This is done by taking the partial derivatives of the Lagrange equation according to the correct variables, and eliminating the results by placing them in the Lagrange equation. The result is a correlation that will be greatest only in Lagrange multipliers (Vapnik,2000).

From the partial derivatives of the primary Lagrange equation according to w, b and ζ_i, Eq. (3.25)- (3.28) are obtained (http-2).

$$\frac{dL_p}{dw} = 0 \Rightarrow w = \sum_{i=1}^{N} a_i y_i x_i = 0 \tag{3.25}$$

$$\frac{dL_p}{db} = 0 \Rightarrow w = \sum_{i=1}^{N} a_i y_i = 0 \tag{3.26}$$

$$\frac{dL_p}{d\zeta_i} = 0 \Rightarrow C - a_i - \mu_i = 0 \tag{3.27}$$

$$L_d = \sum_{i=1}^{N} a_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} a_i a_j\, y_i y_j x_i^T x_j, C > a_i \geq 0, \forall i \tag{3.28}$$

Eq. (3.29) is obtained by using Karush-Kuhn-Tucker (KKT) complementary condition.

$$a_i\left[y_i\big((w \cdot x_i) + b\big) - 1 + \zeta_i\right] = 0, i = 1, \dots., N \tag{3.29}$$

b value in Eq. (3.25) can be expressed as Eq. (3.30).

$$b_i = y_i(1 - \zeta_i) - w \cdot x_i \tag{3.30}$$

There is one Lagrange multiplier for each sample in the training set. The b-value x vectors of the positive-valued Lagrange multipliers obtained during the solution of the equation will form the support vectors and these support vectors are located on the hyperplanes , Eq. (3.25).

Decision function is defined as Eq. (3.31).

$$f(x) = sign\big((w \cdot x_i) + b\big) = sign(\sum_{i=1}^{N} a_i y_i (x \cdot x_i) + b) \tag{3.31}$$

Eq. (3.31) is calculated to test a new data x, and if this total is positive, x is called first class, otherwise x belongs to second class.

3.3.1.2. Nonlinear support vector machine

When the data cannot be separated linearly, the Nonlinear Support Vector Machines transfer the data to a property space of a higher size than the original input space. In this new dimension, it investigates the boundary of decision that best separates the data.

Nonlinear Support Vector Machines decision function is given in Eq. (3.32). In cases where data cannot be differentiated linearly, nonlinear functions are used to analyze the data by moving it to a higher dimensional space.

$$f(x) = sign(\sum_{i=1}^{N} a_i y_i \varphi(x)\varphi(x_i) + b) \quad (3.32)$$

Transformations can be made by using Kernel function expressed as $K(x_i, x_j) = \varphi(x)\varphi(x_i)$ instead of skalar product, $\varphi(x)\varphi(x_i)$, in Eq. (3.32) (Kavzoglu and Colkesen, 2010).

The most commonly used kernel functions are:

1. Linear function: $K(x_i, x_j) = (x_i{}^T x_j)$
2. Polinomial function: $K(x_i, x_j) = (x_i x_j)^d$
3. Sigmoid function: $K(x_i, x_j) = tanh(k x_i x_j - \delta)$
4. Radial basis function: $K(x_i, x_j) = exp\left(-\gamma \|x_i - x_j\|^2\right), \gamma > 0$

3.3.1.3. Multiclass support vector machine

Support vector machine is mainly used for two class data sets. Therefore, problems with K> 2 classes are frequently encountered. As a solution, it is proposed to create a multi-class classifier using different combinations of two classes of Support Vector Machines.

One versus rest method

This is conceptually the easiest multi-class SVM method. Here, class 1 (positive) versus all other classes (negative), class 2 against all other classes, …, class k against all other classes form k binary SVM classifiers. The combined one versus rest (OVR) function selects the sample class that corresponds to the binary decision k functions determined by the subsequent positive hyperplane. By doing so, the decision planes are calculated by k SVM. And it questions the optimization of the multiple category classification. This approach is difficult to calculate, because for us k is the size of the quadratic programming (QP) optimization. The technique does not have theoretical validation, such as generalization analysis, which is relevant to the robust learning algorithm.

One versus one method

This method is related to the creation of binary SVM classifiers of all class pairs. There are three $\left(\frac{k}{2}\right) = \left(\frac{k(k-1)}{2}\right)$ pairs in total. In other words, for each class pair, the binary SVM problem is solved. The decision function assigns an example to a class, then the class it assigns has the highest number of votes, which is called the Max Wins strategy (Friedman, 1996). If there is still a link, an example is assigned to the label based on the classification determined by the subsequent hyperplane. One of the benefits of this approach is that each class pairs have to deal with a smaller optimization problem, and the total k (k-1) / 2 QP problems smaller than n are solved. Assuming that the QP optimization algorithms used for SVMs are of the polynomial type according to the problem size, they provide significant savings in time. In addition, some researchers have identified some binary sub-problems, but not all the multi-category problems, yet have demonstrated that one versus one (OVO) will improve the classification compared to OVR (Kressel, 1999). Unlike the OVR approach, it only plays a minor role in destabilizing equality and has no major impact on the overall decision. On the other hand, similar to OVR, OVO does not currently have the limits set in generalization errors.

There are many multi-class support vector machine methods (Directed Acyclic Graph Support Vector Machine (DAGSVM), Weston and Watkins method, Crammer and Singer method) that have been introduced into the literature with the changes made to these methods, which basically resemble the logic of these two methods.

3.3.1.4. Driver classification by using support vector machine

The attribute vector of the driving data is generated for each driver. A combination of these vectors yielded a 39x3 feature matrix. The training and test matrices needed for the application of the support vector machine method were taken from this matrix. 75% of the available data set is defined as training data set and 25% is defined as test data set. These percentages were selected by examining the literature studies. As a result of the initial classification process, the drives were classified with 100% accuracy. However, in order to prove the accuracy and feasibility of the proposed study, the training and test data were changed with the idea that this method should be tried in the classification process for all available test and training data. By using the leave-p-out method (p=9, n=39), a new set of training and test data was created each time within the attribute matrix and the drives were classified. The process of obtaining training and test data is visualized in Figure 3.7.

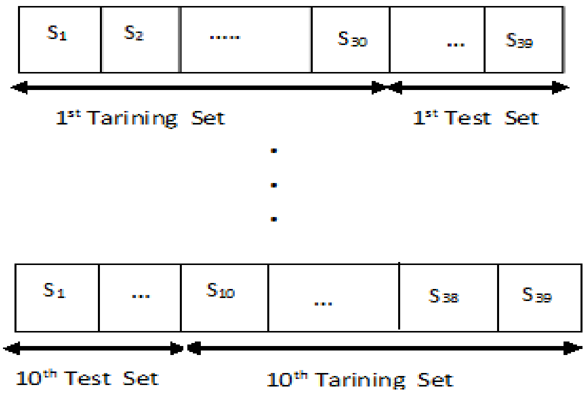


Figure 3.7. *Stage of obtaining of training and test sets*

In the first training set used for classification, Lines 1-30 of the attribute matrix were used, while rows 31-39 were used in the test data set. In the second classification process, the training set which was created by using 2-31 rows and the test set with rows 1 and 32-39 were presented as input to the method. In the last of these procedures, the training set consists of 10-39 Rows and the test data set consists of rows 1-9.First of all, the first 30 lines of the data matrix were created and the training data set was obtained with the remaining 9 lines. Afterwards, training and data sets were changed using leave-p-out cross validation method applied in other methods. In this way, the suitability of the classification for all data has been proved. For example, the training and test data set for the first and final experiments are given in Table 3.3 and Table 3.4, respectively.

Table 3.3. *Traning data sets of first and last classification steps*

	First Classification			Last Classification		
1st Data	27383.8210	8343.1882	2871.5854	29329.2045	9697.6460	2913.3728
2nd Data	27126.4369	8052.3325	2821.4269	27296.8188	9974.7528	2743.9896
3th Data	27245.2549	8700.1209	2816.3529	26713.3265	10296.2812	2629.5596
4th Data	27632.5107	9006.7038	2887.8901	29557.7359	4214.2626	2836.4263
5th Data	21922.0777	3528.3831	2913.4751	26907.7533	4882.1618	3088.4964
6th Data	21533.6939	3673.2568	2733.1964	22418.4302	9073.7968	2659.2370
7th Data	24011.1406	3910.1762	3076.6017	23088.1991	8896.5869	2492.3080
8th Data	22045.7049	3607.8123	2823.3450	27107.3366	10933.0381	2816.0600
9th Data	30031.6753	9909.2231	3339.2539	26588.6761	10504.6090	2595.4167
10th Data	29329.2045	9697.6460	2913.3727	16713.9712	6463.0758	2674.8207
11th Data	27296.8188	9974.7528	2743.9896	15077.2604	5569.4462	2766.3078
12th Data	26713.3265	10296.281	2629.5596	36321.6208	5112.4039	3036.0650
13th Data	29557.7359	4214.2626	2836.4263	28606.5300	4363.0709	2658.9879
14th Data	26907.7533	4882.1618	3088.4964	24642.5759	2963.1430	2293.2266
15th Data	22418.4302	9073.7968	2659.2370	24124.2186	2849.2136	2351.0778
16th Data	23088.1991	8896.5869	2492.3080	23791.1277	3542.0785	2403.3884
17th Data	27107.3366	10933.038	2816.0600	24079.6289	3265.2184	2411.6683
18th Data	26588.6761	10504.609	2595.4167	23212.5083	3094.4938	2369.7311
19th Data	16713.9712	6463.0758	2674.8207	23095.2506	2822.4979	2473.4978
20th Data	15077.2604	5569.4462	2766.3078	25118.0058	5497.2100	2812.3014
21th Data	36321.6208	5112.4039	3036.0650	27827.2088	10474.7006	2687.9523
22th Data	28606.5300	4363.0709	2658.9879	28486.2995	10555.7210	2703.8158
23th Data	24642.5759	2963.1430	2293.2266	27672.9616	5190.6188	2752.4948
24th Data	24124.2186	2849.2136	2351.0778	26584.87066	5448.8068	2680.6193
25th Data	23791.1277	3542.0785	2403.3884	22492.56556	4938.2072	2694.4651
26th Data	24079.6289	3265.2184	2411.6683	22912.30176	4720.6937	2738.7521
27th Data	23212.5083	3094.4938	2369.7311	23437.36484	4826.9385	2645.9003
28th Data	23095.2506	2822.4979	2473.4978	22909.75965	4714.3612	2660.5308
29th Data	25118.0058	5497.2100	2812.3014	15699.43727	2627.4373	2572.9282
30th Data	27827.2088	10474.700	2687.9523	13720.89143	2663.6334	2583.0852

Table 3.4. *Test data sets of first and last classification steps*

	First Classification			Last Classification		
1st Data	28486.2995	10555.721	2703.8158	27383.8210	8343.1882	2871.5854
2nd Data	27672.9616	5190.6188	2752.4948	27126.4369	8052.3325	2821.4269
3th Data	26584.8706	5448.8068	2680.6193	27245.2549	8700.1209	2816.3529
4th Data	22492.5655	4938.2072	2694.4651	27632.5107	9006.7038	2887.8901
5th Data	22912.3017	4720.6937	2738.7521	21922.0777	3528.3831	2913.4751
6th Data	23437.3648	4826.9385	2645.9003	21533.6939	3673.2568	2733.1964
7th Data	22909.7596	4714.3612	2660.5308	24011.1406	3910.1762	3076.6017
8th Data	15699.4372	2627.4373	2572.9282	22045.7049	3607.8123	2823.3450
9th Data	13720.8914	2663.6334	2583.0852	30031.6753	9909.2231	3339.2539

The average accuracy was 98.9% as a result of the classifications made with the matrices obtained in this way in order to have the drivers in all classes in the training set. Only one of the 90 drives in the test matrix was classified as incorrect. In other words, the probability of a driver in a wrong class is 0.011. In Table 3.5, the accuracy of the method is given for different classes.

Table 3.5. *Accuracy of proposed method*

Driver Class	Correct Classification Percentage
Moderate	100
Conservative	100
Aggressive	97.82

Since it is important to have approximately the same number of drivers in all classes in the training data, the driver class distributions in the test phase cannot be realized equally. The classification results are given in Table 3.6.

Table 3.6. *Confusion matrices*

Test No	Real classes of drivers			
	Conservative	Moderate	Aggressive	Predicted classes of drivers
1st Test	3	0	0	Conservative
	0	0	0	Moderate
	0	0	6	Aggressive
2nd Test	3	0	0	Conservative
	0	0	0	Moderate
	0	0	6	Aggressive
3rd Test	3	0	0	Conservative
	0	0	0	Moderate
	0	0	6	Aggressive
4th Test	3	0	0	Conservative
	0	0	0	Moderate
	0	0	6	Aggressive
5th Test	4	0	0	Conservative
	0	0	0	Moderate
	0	0	5	Aggressive
6th Test	4	0	0	Conservative
	0	0	0	Moderate
	0	0	5	Aggressive
7th Test	4	0	0	Conservative
	0	0	0	Moderate
	0	0	5	Aggressive
8th Test	4	0	0	Conservative
	0	1	0	Moderate
	0	0	4	Aggressive
9th Test	4	0	0	Conservative
	0	1	0	Moderate
	0	0	4	Aggressive
10th Test	5	0	1	Conservative
	0	1	0	Moderate
	0	0	2	Aggressive

3.3.2. Markov chain

The process that consists of the values that a random variable takes at consecutive moments over time (or consecutive points in space) is called stochastic process. The variable X of a stochastic process is expressed by the values x_1, x_2, x_3 .... measured at

Δt time intervals t_1, t_2, t_3 (or s_1, s_2, s_3,…points in space with Δs steps). These values are not independent of each other in many processes.

The process created by taking into account the effect of a random variable (which can take one of a finite number) in consecutive moments (or consecutive points in space) over time in one of a finite number of states is called Markov Chain. Let the process be represented by the values $(X_0 = x_0, X_1 = x_1, X_2 = x_2, \dots.)$ in $t_0, t_1, t_2 \dots$ moments. The probability that this process exists at state j at time t_{n+1} can be written as conditional probability $P\left(X_{n+1} = x_j \middle| X_0 = x_0, X_1 = x_1, X_2 = x_2, \dots . X_n = x_n\right)$. If this probability is equal to the conditional probability $P\left(X_{n+1} = x_j \middle| X_n = x_n\right)$, the state transition probability equation can be written as Eq. (3.33).

$$P(X_{n+1} = j|X_0 = x_0, X_1 = x_1, X_2 = x_2, \dots . X_n = x_n) = P(X_{n+1} = j|X_n = x_n) \quad (3.33)$$

This means that the value of the random variable of the process at any time t_{n+1} depends only on the value of the previous t_n. That is, the states in which the process was present in the previous moments $t_{n-1}, t_{n-2}, \dots$ do not directly affect the situation at the moment t_{n+1}. The process with such a feature (first order, simple) is called Markov Chain (Aksoy, 1998). The Markov chain is a simple form of internal dependence in processes. In a Markov chain ($n > m$), the probability of transition from state i in t_m to state j in t_n can be shown as $P_{ij}(m, n)$ and this probability is equal to Eq. (3.34).

$$P_{ij}(m, n) = P(X_{n+1} = j|X_m = i), \; n > m \quad (3.34)$$

If the Markov chain is homogeneous, the probability of $P_{ij}(m, n)$ depends only on the time elapsed between t_m and t_n. The k-step transition probability function of a homogeneous chain is given in Eq. (3.35).

$$P_{ij}(k) = P(X_{t+k} = j|X_t = i), \; k > 0 \quad (3.35)$$

The P_{ij} probabilities can be considered as elements of the **P** transition probabilities matrix. The matrix **P** in the mxm dimension is expressed as Eq. (3.36).

$$\mathbf{P} = P_{ij} = \begin{bmatrix} P_{11} & P_{12} \dots & P_{1m} \\ P_{21} & P_{22} \dots & P_{2m} \\ \vdots & \vdots & \vdots \\ P_{m1} & P_{m2} \dots & P_{mm} \end{bmatrix} \quad (3.36)$$

The sum of the elements on a row in the matrix is equal to 1. Because these elements indicate the probability that the process which is in a certain state at t will be able to transate to various states at t + 1.

3.3.2.1. Driver classification by using markov chain

The conditions needed for the grading process by Markov method were created from the raw form of the velocity and angular velocity data. The 20 cases given in Table 3.7 are identified. These 20 cases are determined by considering the change intervals of the data obtained from the drives. Figure 3.8 shows the angular speed graph of an example driver and Figure 3.9 shows the angular speed distribution graph for this ride.

Table 3.7. *Markov states*

States	Change in speed(ΔV)	Angular velocity(ω_x)
State 1	$\Delta V<0$	$\omega_x<-2$
State 2	$\Delta V<0$	$-2\leq\omega_x<-1.5$
State 3	$\Delta V<0$	$-1.5\leq\omega_x<-1$
State 4	$\Delta V<0$	$-1\leq\omega_x<-0.5$
State 5	$\Delta V<0$	$-0.5\leq\omega_x<0$
State 6	$\Delta V<0$	$0\leq\omega_x<0.5$
State 7	$\Delta V<0$	$0.5\leq\omega_x<1$
State 8	$\Delta V<0$	$1\leq\omega_x<1.5$
State 9	$\Delta V<0$	$1.5\leq\omega_x<2$
State 10	$\Delta V<0$	$2\leq\omega_x$
State 11	$\Delta V\geq0$	$\omega_x<-2$
State 12	$\Delta V\geq0$	$-2\leq\omega_x<-1.5$
State 13	$\Delta V\geq0$	$-1.5\leq\omega_x<-1$
State 14	$\Delta V\geq0$	$-1\leq\omega_x<-0.5$
State 15	$\Delta V\geq0$	$-0.5\leq\omega_x<0$
State 16	$\Delta V\geq0$	$0\leq\omega_x<0.5$
State 17	$\Delta V\geq0$	$0.5\leq\omega_x<1$
State 18	$\Delta V\geq0$	$1\leq\omega_x<1.5$
State 19	$\Delta V\geq0$	$1.5\leq\omega_x<2$
State 20	$\Delta V\geq0$	$2\leq\omega_x$

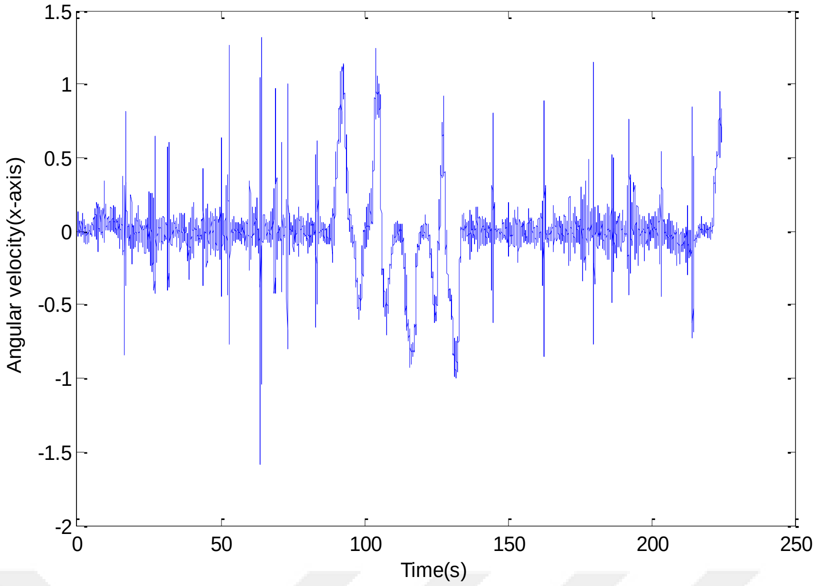


Figure 3.8 *x-axis angular velocity of a driver*

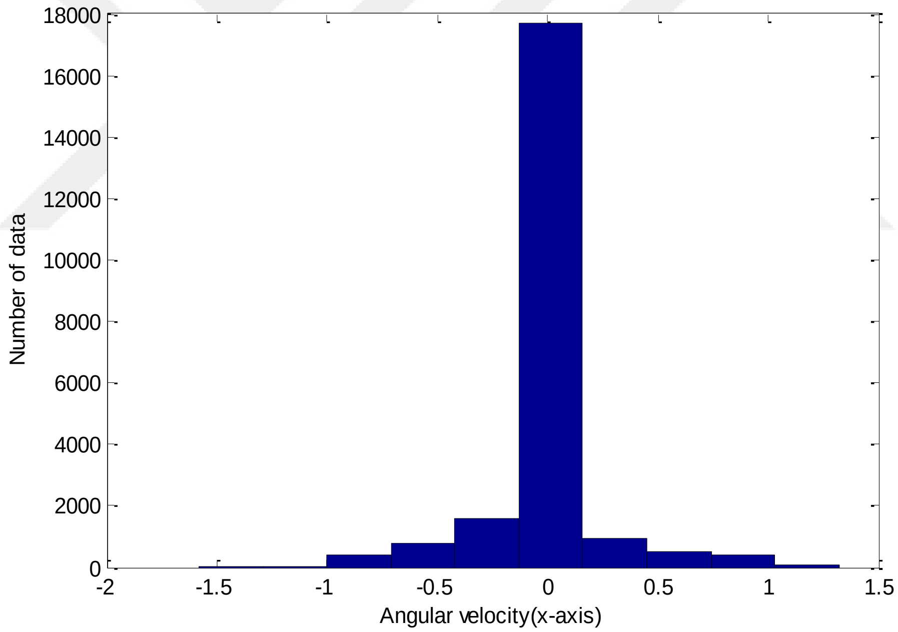
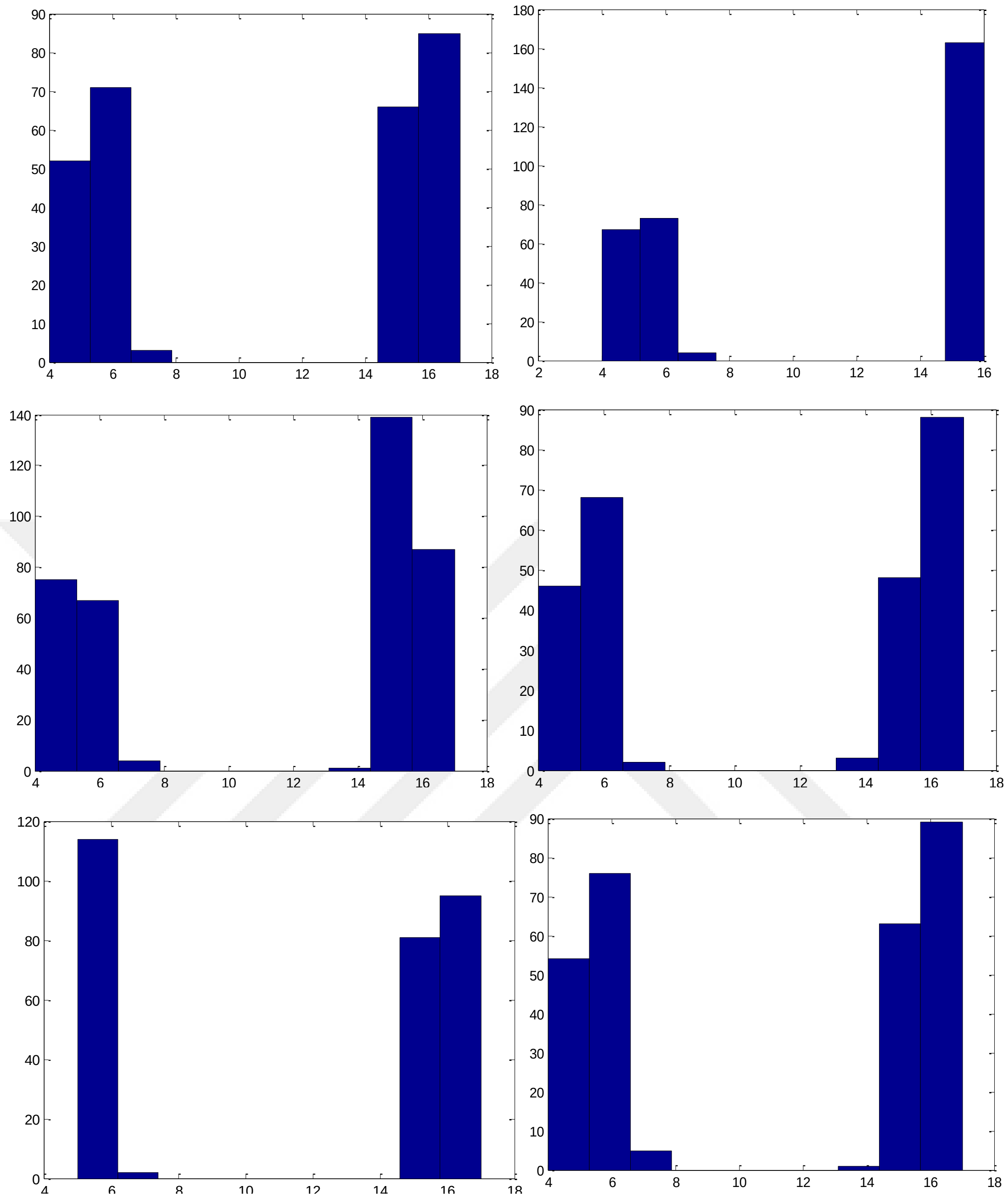


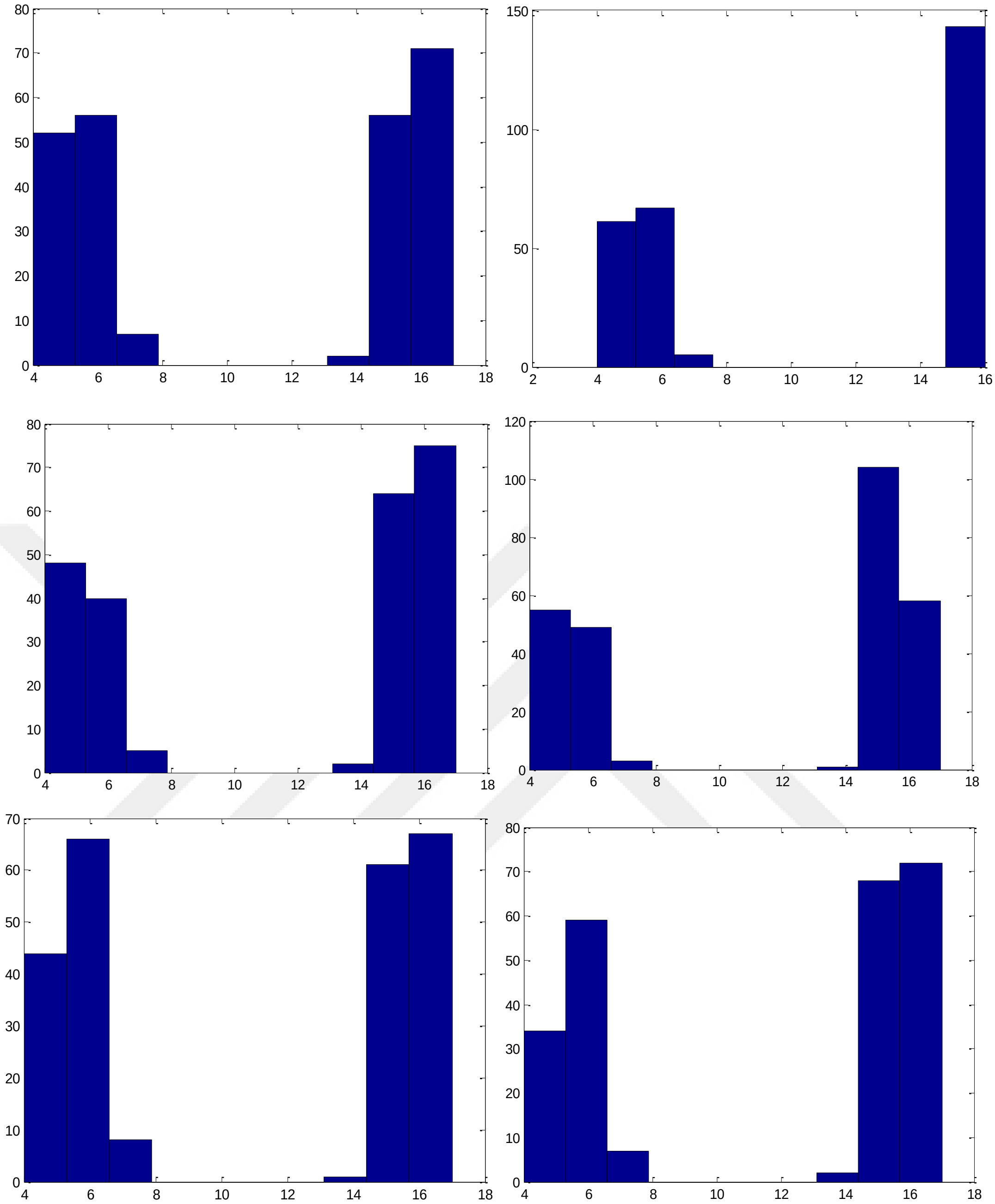
Figure 3.9. *Histogram of x-axis angular velocity*

Together with the determination of the states, the states were created for all rides and the state transition matrices were obtained. States distribution graphs of 6 different drives from all drive classes are given in Figure 3.10.



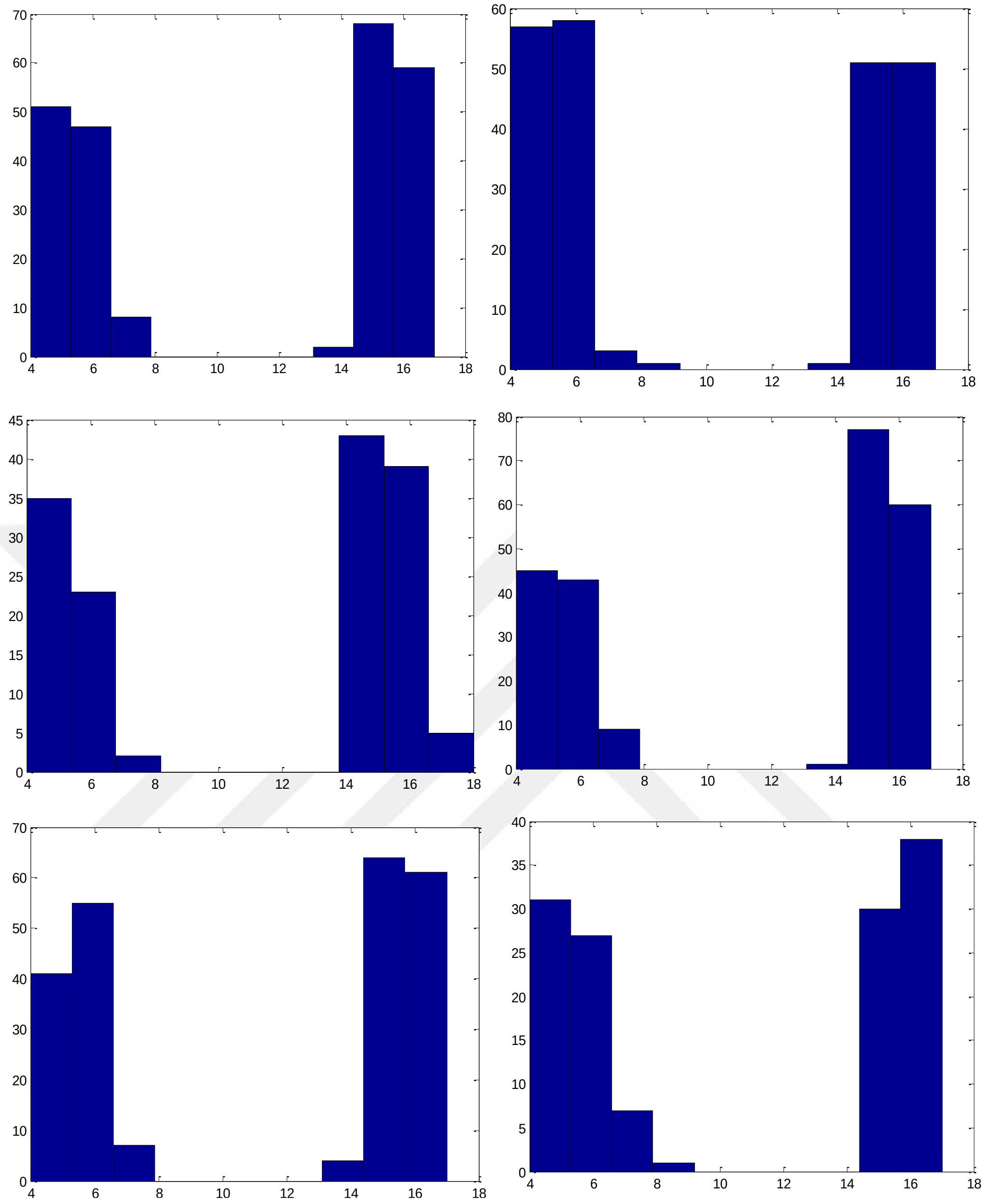
(a)

Figure 3.10. *The states of different drivers(a-conservative, b-moderate, c-aggressive)*



(b)

Figure 3.110. (Continue) *The states of different drivers(a-conservative, b-moderate, c-aggressive)*



(c)

Figure 3.10. (Continue) *The states of different drivers(a-conservative, b-moderate, c-aggressive)*

Considering the states given above as an example, a state transition probability matrix was obtained for all drives. In Table 3.8, Table 3.9 and Table 3.10, sample probability transition matrices are given for the drivers in the conservative, moderate and aggressive classes, respectively.

Table 3.8. *Transition probability matrix of a conservative driver*

States	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
5	0	0	0	0.04	0.48	0.26	0	0	0	0	0	0	0	0	0.12	0.1	0	0	0	0
6	0	0	0	0	0.15	0.63	0.014	0	0	0	0	0	0	0	0.07	0.12	0	0	0	0
7	0	0	0	0	0	0	0.33	0	0	0	0	0	0	0	0	0	0.66	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0.18	0.03	0	0	0	0	0	0	0	0	0.54	0.24	0	0	0	0
16	0	0	0	0	0.036	0.13	0.012	0	0	0	0	0	0	0	0.2	0.60	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 3.9. *Transition probability matrix of a moderate driver*

States	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0.5	0	0	0	0	0	0	0	0	0	0	0.50	0	0	0	0	0
5	0	0	0	0.017	0.48	0.267	0	0	0	0	0	0	0	0	0.178	0.03	0	0	0	0
6	0	0	0	0	0.2	0.38	0.03	0	0	0	0	0	0	0	0.07	0.25	0	0	0	0
7	0	0	0	0	0	0	0.2	0	0	0	0	0	0	0	0	0.25	0.5	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0.14	0.07	0	0	0	0	0	0	0	0.01	0.62	0.15	0	0	0	0
16	0	0	0	0	0.03	0.14	0	0	0	0	0	0	0	0	0.36	0.45	0	0	0	0
17	0	0	0	0	0	0.50	0.50	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 3.10. *Transition probability matrix of a aggressive driver*

States	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0.42	0.28	0	0	0	0	0	0	0	0	0.14	0.14	0	0	0	0	0
5	0	0	0	0.06	0.26	0.32	0	0	0	0	0	0	0	0	0.22	0.14	0	0	0	0
6	0	0	0	0	0.27	0.34	0	0	0	0	0	0	0	0	0.10	0.24	0.01	0	0	0
7	0	0	0	0	0	0	0.33	0.33	0	0	0	0	0	0	0	0	0.33	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
15	0	0	0	0.02	0.29	0.13	0	0	0	0	0	0	0	0	0.37	0.17	0	0	0	0
16	0	0	0	0	0.08	0.31	0.04	0	0	0	0	0	0	0	0.22	0.33	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.66	0.33	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Cells containing meaningful information were determined by examining the transition probability matrices of the classes. These cells make themselves meaningful in the form of regular increases or decreases between classes. When the values of these cells are evaluated appropriately, it is thought to make a significant contribution in driver classification. A weighted arithmetic mean of the cells was defined and a distinctive attribute was defined for the classes.

Weighted arithmetic mean

The weighted arithmetic mean of a set of numbers X_1, X_2, ..., X_N with respective weights of w_1, w_2, ..., w_N is defined as Eq. (3.37).

$$\bar{X} = \frac{w_1 X_1 + w_2 X_2 + \cdots + w_N X_N}{w_1 + w_2 + \cdots + w_N} \tag{3.37}$$

When the fifth feature was developed, the dominant conditions of each driving class were determined be examining the state transition probabilities of the drivers. Taking these dominate states into account, the weighted arithmetic mean of the state transition probability matrices is taken. Table 3.11 shows the weighted arithmetic mean values of all driving.

Table 3.11. *Weighted arithmetic mean of transition probility matrices*

Drive no	Weighted arithmetic mean
1st Drive	0.0364
2nd Drive	0.0415
3thDrive	0.0293
4thDrive	0.0216
5thDrive	0.0403
6thDrive	0.0806
7thDrive	0.0771
8thDrive	0.0606
9thDrive	0.0292
10thDrive	0.0503
11thDrive	0.0454
12thDrive	0.0543
13hDrive	0.0299
14thDrive	0.0319
15thDrive	0.0431
16thDrive	0.0533
17thDrive	0.0492
18thDrive	0.0504
19thDrive	0.0547
20thDrive	0.0522
21thDrive	0.0576
22thDrive	0.0316
23thDrive	0.0410
24thDrive	0.0446
25thDrive	0.0440
26thDrive	0.0502
27thDrive	0.0502
28thDrive	0.0466
29thDrive	0.0446
30thDrive	0.0428
31thDrive	0.0411
32thDrive	0.0576
33thDrive	0.0357
34thDrive	0.0438
35thDrive	0.0554
36thDrive	0.0554
37thDrive	0.0539
38thDrive	0.0357
39thDrive	0.0429

The values in the table were added to the SVM data matrix as Feature 4 and the classification was re-performed for the 39x4 data matrix. Considering attribute 4, classification accuracy is reduced. Wrong classification was made for 7 drives and accuracy decreased to 92.2%.

3.3.3. K nearest neighbor method

The k-nearest neighbor method was first introduced by Fix and Hodges (1951) as a non-parametric method for use in pattern recognition and later developed by Cover and Hart (1967). K-nearest neighbor method is a classification method that determines the class where the observations will take place and the nearest neighbor according to the k-value. It is one of the supervised data mining algorithms that classify based on observations or distance between objects. The method is used in many areas such as pattern recognition, artificial intelligence, data mining, statistics, cognitive psychology, medicine, and bioinformatics (Fix and Hodges, 1951; Cover and Hart, 1967).

The K-nearest neighbor algorithm makes the classification by distance or proximity calculation. In summary, this classification algorithm is based on the idea that "objects that are close to each other in the sample space probably belong to the same category". The purpose of the algorithm is to assign individuals or objects to the predetermined classes or groups in the most accurate way, using the properties of those objects. The method also allows for the classification of a new observation. With the help of the learning data set, the observation to be classified is classified in the same data set with the most similar ones among the closest k observations. The data set to be used in the formation of a model is called the learning data set (Fix and Hodges, 1951; Cover and Hart, 1967; Harrington, 2012).

K-nearest neighbor method has many advantages such as providing clear and effective results, being able to ignore missing observations in continuous variables, having the option to evaluate missing observations in categorical variables, and being able to provide categorical, continuous or a combination of both. Also, it has disadvantages such as the number of closest neighbors, the number of k required, influenced by the selected distance measurement, the lack of accuracy of the distance to be used (Elasan,2019).

The K-nearest neighbor algorithm is used to classify observations according to their similarity to other phenomena. It was developed as a way of recognizing data models without exact matching to learned patterns or models. Similar observations are close (neighbors) and dissimilar observations are distant from each other. Therefore, the distance between the two observations is a criterion determining the dissimilarity. The distances of a new observation from the observations in the model are calculated. This observation is assigned to the most repetitive/similar category (Fix and Hodges, 1951; Cover and Hart, 1967).

When performing this method, the following steps are performed (Cover and Hart; 1967; http-3):

1. The distance of the new observation to all observations in the data set is calculated,
2. These distance values are sorted,
3. k observations with the smallest distance are selected,
4. In k observation, the majority voting category is the class value.

In addition to obtaining the class value with the majority voting category in K observation, weighted voting can also be used. As shown in Eq. (3.38), the inverse or inverse square of the distances is used as weight. With the help of the weights calculated for each class, the category with the highest weight is selected as the class value. x_i and x_q represent observations in the learning data set and test sample, respectively.

$$W = \frac{1}{d(x_q,x_i)^2} \tag{3.38}$$

At the beginning of the classification process, the data is converted to numerical values and the number of nearest neighbor (k) is determined. When determining the class of observations in the test sample, the distances of each observation to the observations in the learning data set are calculated and the closest k observations are selected. When calculating the distance, different distance measurements such as Euclid, Manhattan (City Block), Minkowski, Chebyshev, Dilca can be utilized (Fix and Hodges, 1951; Cover and Hart, 1967; http-3).

The K-nearest neighbor algorithm optionally divides the data into two sets: training and test (holdout). The learning data set is used in the formation of the model. The test data set is used to evaluate the model independently. Incomplete observations of continuous variables can be ignored. Categorical variables have the option of evaluating missing observations. The number of categories can be reduced by combining similar categories or subtracting less observed categories before applying the model. In addition, contradictory observations can be removed from the model (Fix and Hodges, 1951; Cover and Hart, 1967).

In k-nearest neighbor algorithm, forward selection method is used for variable selection to algorithm. Variables are selected sequentially, and the variable selected at each step is the variable that ensures that the error rate or the sum of the error squares is minimum (Cover and Hart, 1967; Cunningham and Delany, 2007).

When a new variable is added to the model, the algorithm stops when it is understood that the model cannot be further developed (Cover and Hart, 1967).

3.3.3.1. Selection of the number k

The K nearest neighbor algorithm uses the nearest neighbor samples to classify or predict observations in the n-dimensional property space. In the K-nearest neighbor algorithm, a positive integer such as k indicates how many closest neighbor numbers to consider in order to classify the new observation. If k = 1, the new observation attempted to be classified will be included in the class of the nearest neighbor. This method is also used for estimation. As the number K approaches the number of instances (N), the assignment (classification) is made to the category with more than adjacent objects. When all the data in the data set are considered, the assignment is made to the most repeating category. In short, k is the number of closest neighbors to be considered in the classification of a new observation (Cover and Hart, 1967).

3.3.3.2. Similarity, distance and proximity measurements

Similarity is a numerical magnitude that reflects the strength of the relationship between two properties or objects, which is very difficult to measure. This size is usually in the range of ±1 and can be normalized to a range of 0 to +1. Distance measures dissimilarity. The dissimilarity can also be considered as a measure of the mismatch between two objects. These measures can also be used as coordinate values in the properties space for the object. At the beginning of the classification process, the data is converted to numerical values and the number of nearest neighbor (k) is determined.

When determining the class of observations in the test sample, the distance from the observations in the learning data set is calculated and the closest k observations are selected (Cover and Hart; 1967; Teknomo, 2006; Cunningham and Delany, 2007). When calculating the distance, different distance measurements such as Euclid, Manhattan (City Block), Minkowski, Chebyshev, Dilca can be utilized (Fix and Hodges, 1951; Cover and Hart, 1967; http-3).

Distance measurements differ if the data includes continuous and/or categorical variables. If the variables are continuous and categorical, the commonly used measures for the distance between observations are Euclid and Manhattan. It is recommended to use Euclidean distance function if the data set contains continuous variables in all dimensions, and to use Manhattan distance function if it includes categorical variables (http-4). In this context, in the study, Euclidean (City Block) measurement was used by taking into consideration the data type.

Euclidean distance is the linear distance between two points, such as x and y. Calculated as the square root of the sum of the weighted square differences between the observation values over all dimensions. d, to indicate the distance between the x and y points; equation of Euclidean distance measure is as Eq. (3.39) (http-4).

$$d(x,y) = \sqrt{\left(\sum_{j=1}^{N}\left(x_j - y_j\right)^2\right)} \tag{3.39}$$

The distance between objects can be any measure of distance. The first problem that comes to mind in finding proximity is to find the closest points in a given set of points. The most preferred models for these measurements are Voronoi diagram and Delaunay triangulation. These models, which have found application in many areas, are generally related to the finding of proximity points of all points to a point (McAllister and Snoeyink, 2000).

3.3.3.3. Driver classification by using KNN

Since the correct classification of the drivers is of great importance in this thesis, the k-Nearest Neighbor algorithm is considered as an alternative classification method. In this method, the data used in other methods were used. The obtained attributes were presented to the classification algorithm as data matrix.

The different data sets obtained in this way show that the attributes we propose provide meaningful results for different data. After determining that the diagnoses on the data set were sufficient, the determination of the k value, which is the important parameter related to the classification method, was examined. Euclidean distance measure is used since the data set is continuous time data. The drives are classified by selecting different k values. Among these values, the number of neighbors with the highest accuracy was determined and operations were made on this value while moving on to the next stage of the study. The accuracy percentage is defined by Eq. (3.40).

$$Accuracy = \frac{Number\ of\ correctly\ estimated\ drivers}{Number\ of\ all\ drivers} \tag{3.40}$$

The classification accuracy obtained for all k values is given in Table 3.12.

Table 3.12. *Accuracy of classification for different k values*

k value	Accuracy(%)
k=1	85.555
k=3	83.333
k=5	93.333
k=7	91.111
k=9	90
k=11	74.444

When the accuracy curve given in Figure 3.11 is examined, it is seen that the global maximum point is obtained for k = 5 value. Accuracy values before and after this value decrease.

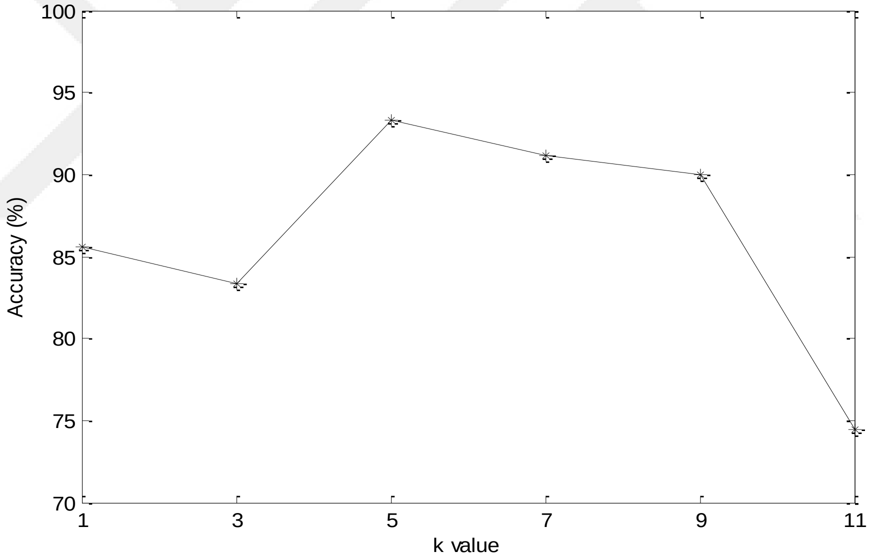


Figure 3.11. *Accuracy of classification for different k values*

Confusion matrices for all k values are given in Table 3.13.

Table 3.13. *Confusion matrices*

k Value	Real classes of drivers				
	Conservative	Moderate	Aggressive		
k=1	3	5	8	Conservative	**Predicted classes of drivers**
	0	32	0	Moderate	
	0	0	42	Aggressive	
k=3	3	2	13	Conservative	
	0	35	0	Moderate	
	0	0	37	Aggressive	
k=5	3	0	6	Conservative	
	0	37	0	Moderate	
	0	0	44	Aggressive	
k=7	3	2	6	Conservative	
	0	35	0	Moderate	
	0	0	44	Aggressive	
k=9	0	2	4	Conservative	
	0	35	0	Moderate	
	3	0	46	Aggressive	
k=11	0	4	16	Conservative	
	0	33	0	Moderate	
	3	0	34	Aggressive	

In order to have approximately equal number of driver information from all classes in the training data set, the drive distributions in the test data are not equal. Since the minority of drivers participating in the rides is in the conservative class, the lowest number in the confusion matrix is in the conservative class cells.

4. ELECTRIC VEHICLES

With the growth of industrialization, transportation has become a great necessity for humanity. It is not possible to say the name of a single person in the emergence of cars. Cars have been developed from the past to the present, with the ideas, imagination and excitement of hundreds of people over hundreds of years. In the early years of the development of the car, there was a sharp competition between gasoline, steam and electric vehicles. This innovation has led to more innovations with the emergence of a wide range of manufacturers and entrepreneurs. Increasing interest in automobiles and meeting the needs of people, supplying a wide range of public vehicles has increased the excitement of several entrepreneurial manufacturers (Albal, 2018).

The history of electric vehicles can generally be divided into three parts: the early years (1830-1929), dominance in the market between 1895-1905, the golden age, the middle years (1930-1989); and current years (1990 to present).

The first electric vehicle came into being in the 1830s with disposable batteries. Afterwards, there has been no study on the efficient use of batteries in electric vehicles for about half a century. By the end of the 19th century, electric vehicles were widely used with the mass production of rechargeable batteries. In these years, electric vehicles constitute personal vehicles and rarely even taxi vehicles. England and France became the first countries to test electric vehicles, and America became interested in 1895. The first electric vehicle can be regarded as the transformed tricycle created by M. Raffard in France in 1881. In 1897, New York City taxi fleet, the first commercial application of electric vehicles in the United States, was built by Filedelfiya Electric transport and wagon company.

The general perception of the electric vehicle in 1899 was that it had many advantages over gasoline cars: clean, quiet, vibration-free, completely reliable, easy to start and control, free of dirt and odors. The disadvantages were short range and high initial cost. The batteries were not cheap and only had an average range of about 18 miles per day. However, it met the needs of most of the population in these big cities. In 1899 and 1900, electric vehicles left behind all other types of cars in America. Between 1895 and 1914, a wide range of cars was built with different body styles and engine configurations. As the 1920s approached, the end of what could be called the experimental age for electric cars came. It almost ended as habitable sources of steam and electricity.

Electric cars had market in Europe before the US. The first car entered production in 1885 is thought to be the German single-cylinder Benz petrol three-wheeler. Gottlieb Daimler produced a four-wheel, petrol car in Stuttgart, Germany. In 1886, Andrew L. Riker was the first American to produce an electric vehicle. It was a tricycle imported from the UK, fitted with an engine that provided 1/6 horsepower and speed at eight miles per hour at about thirty miles. The United States did not have a manufacturing industry until 1896, when the Duryea brothers in Springfield, Massachusetts, produced thirteen matching "motor wagons".

In 1900, France led the world in automobile production, innovation and ownership. There were 5,600 cars in France, 3,939 stores and only 265 electric charging stations for support infrastructure, oil, gas and other necessities. New York State had about 4,000 registered vehicles in 1903. Of these, 53 percent were supplied with steam (primarily Locomobile Company), 27 percent with gasoline, and 20 percent with electricity. Automobile production was about to explode in the United States, and the proportion of support stations associated with gasoline and electric vehicles remained the same in 1900 as France.

In Turkey, the first electric car to Messrs Immisch & Co. in the United Kingdom were ordered by Abdul Hamid in 1888. Engineered by the company's engineers Magnus Volk and Moritz Immisch, this car had two smaller wheels close to each other instead of a single big wheel, with a 20-amp, 48-volt, 1-horsepower engine patented by Immisch. Abdulhamid was very pleased with this car and rewarded these two engineers, so that the engineers had gained an international reputation.

One of the solutions to overcome the lack of charging infrastructure that lasted until 1896 was the first time the Hartfor Electric Light Company introduced the replaceable battery service for electric trucks. The owner purchased his vehicle without batteries from General Electric and purchased the electricity from Hartfor Electric through replaceable batteries. The vehicle owner paid a variable charge per mile and a monthly service charge that included truck storage and maintenance. Between 1910 and 1924, the service offered more than 6 million miles of transport. In early 1917, a similar service was available to owners of Milburn Light Electric cars in Chicago to purchase battery-free vehicles.

When it comes to performance, electric vehicles are preferred over internal combustion engines and steam-powered competitors. Before internal combustion engines take over, electric cars have many speed and distance records. The most notable of these records is the breaking of the 100 km/h record by 106 km/h with Camille Jenatzy on April 29, 1899 with his rocket-type vehicle La Jamais Contente.

At the beginning of the 20th century, electric vehicles were a strong competitor in future road transport. Although slower than internal combustion engines, it was preferred in the early 1900s due to some advantages. The negative aspects such as shaking, smell and noise found in petroleum cars did not exist in electric vehicles. Electric cars did not have the problem of changing gear, which is the biggest problem when driving in oil cars. Electric cars were preferred in a way that the rich people would not need long range in urban transportation. Another disadvantage of petroleum automobiles was that it needed a manual lever to start the engine, which required physical effort to set it up. For this reason, electric cars provide ease of use for ladies. Another option, steam-powered vehicles, needed lighting and their thermal efficiency was relatively low.

In the 1920s, hundreds of thousands of electric vehicles were produced to be used as cars, minibuses, taxis, commercial vehicles and buses. Despite all these developments, the spread of cheap oil and the invention of the self-starter for internal combustion engines (1911) made the internal combustion engine a more attractive vehicle.

The reasons for the success of internal combustion engines are easily understood when the specific energy of the petroleum fuel is compared with the specific energy of the batteries. The specific energy of the lead acid battery is 30 $Whkg^{-1}$, while the specific energy of the oil is 9000 $Whkg^{-1}$. When the gearbox and gearbox efficiency, which is 20% efficient on the efficiency of an internal combustion engine, is calculated, 1800 $Whkg^{-1}$ of useful energy can be obtained from gasoline. In electric motors with 90% efficiency, only 27 $Whkg^{-1}$ of energy can be obtained from the lead acid battery in the transmission shaft.

In terms of range, 4.5 liters (approximately 4 kg in weight) of oil and an internal combustion engine can drive 50 km. On the electric motor side, a lead acid battery with a mass of approximately 270 kg is required to store the same amount of energy. There will be a need for extra energy to climb, accelerate and slow down. Some energy can be obtained from the regenerative braking system, where the engine acts as a generator and braking converts kinetic energy into electrical energy. In practice, however, less than one-third of the spent energy can be recycled. As a result, there is a need for a 2.7 ton lead acid battery equivalent to a 45-liter fuel tank in order to be an efficient electric vehicle close to the internal combustion engine. This makes the regenerative braking system suitable for heavy vehicles rather than passenger cars. 2.7 tons of lead acid batteries, which have the same efficacy as 45 liters of oil, cost 8000 pounds at today's prices. In addition, the batteries have a limited life span (approximately 5 years), thus causing periodic replacement costs. When all these reasons are taken into consideration, the reasons why internal combustion engines are preferred in the 20th century are clearly understood.

Since the 19th century, solutions have been sought to overcome the limited energy capacity problem of batteries. The first is to supply electrical energy through supply rails. The best example is trolleybuses. This solution has been widely used in the 20th century and has been preferred frequently due to its silence and environmental pollution in cities and small residential areas. Trolleybuses can be operated with their own batteries when away from power lines. The downside of this situation is the supply lines which are quite expensive and also visually unpleasant. As a result, most trolleybus and tram systems were decommissioned.

In the early years of the development of electric vehicles, the hybrid vehicle concept was developed to use an internal combustion engine operating a generator with one or more electric motors. Hybrid vehicles have undergone a lot of trials in the early 20th century, but have recently gained popularity. Hybrid vehicles are the most promising development that can revolutionize the impact of electric vehicles. Developments in this area are important for the future.

The Clean Air Act required automotive manufacturers to produce more partial electric (hybrid) and fully electric cars. The main objective of the law is to improve the quality of air in urban areas, such as Southern California, where air pollution is a major problem. Clean fuel vehicles have been shown to be beneficial in reducing the amount of air pollution in certain regions of the United States. It brought renewed attention to air quality and the environmental impact of the internal combustion engine, such as regulations introduced by the California Air Resources Board (CARB) in 1990. Since 2002, regulations have encouraged research in electric vehicles and revitalized the development of environmentally friendly vehicles through tax incentives, grants and collaborative projects in the government industry.

Each period, electric vehicles were introduced with quiet, reliable, environmentally friendly advantages compared to their competitors. In today's conditions, both general carbon dioxide emissions and the emission of exhaust fumes are an important concern for people living in crowded cities. From this point of view, electric vehicles have a great advantage over internal combustion engines. Another important issue at this point is the technological developments in rechargeable batteries. The refueling batteries developed by William Groove in 1840 and whose efficiency is increased by technological developments will play a major role in the spread of electric vehicles.

Environmental problems play a major role in urban use, and electric vehicles will be the best alternative for cities where leaded gasoline is banned and zero-emission vehicles are encouraged. At this point, the method used in electricity supply is of great importance. When fossil fuels are burned in electricity supply, there is no significant difference between the environmental hazards of electric vehicles and diesel or gasoline-powered vehicles. However, preferring alternative energy sources such as hydrogen or wind in the supply of electricity will support the environmentally friendly conditions of electric vehicles. At the same time, the prospect of improvements in range and cost, as well as ongoing development of battery technology, is a valid reason for the increased use of electric vehicles.

4.1. Advantages and Disadvantages of Electric Vehicles

Electric vehicles are quiet and environmentally friendly (Keskin, 2014). There is no emission of harmful gases (http-5). While the efficiency in internal combustion engine vehicles is 40%, the efficiency in electric vehicles is 90%. Thanks to the high torques of the electric motors, these vehicles which work with high efficiency accelerate the vehicle in a shorter time than vehicles with internal combustion engines (Khajepour et al., 2014). Electric vehicles have simple structures. These vehicles do not require structures such as gearbox, exhaust system, cooling. Electric vehicles are capable of adapting to future technologies (Keskin, 2014).

Batteries can be charged with the ability of electric motors to generate electricity in braking and downhill situations (Karaoğlan, 2014). The cost of electric motors is inexpensive, long-term usability and easy to replace (Keskin, 2014). In spite of all these advantages, they have some disadvantages such that the weight of the batteries is high and the cost is high, some structures need to be renewed after 4-5 years, the full charging time lasts 7-8 hours (Keskin, 2014; Karaoğlan, 2014; Başer, 2016). However, thanks to the developing technology, these problems are tried to be eliminated. For electric vehicles using lithium-ion batteries, the charging time is 1 to 3 hours using fast charging technology (Başer, 2016).

4.2. Optimization of Electrical Vehicle Parameter

Electric vehicles having a simpler mechanical structure compared to gasoline vehicles are driven by one or more electric motors and receive the power they need from an on-board source of electricity. Another advantage of gasoline vehicles is that it causes less environmental pollution. Moreover, it is more durable thanks to its structure. An electric automobile uses mainly batteries as an energy storage, but capacitors and flywheel storage devices are used as alternative energy storage devices. When the components of the electrical vehicle (Figure 4.1) are examined, arrangements will be made for these components.

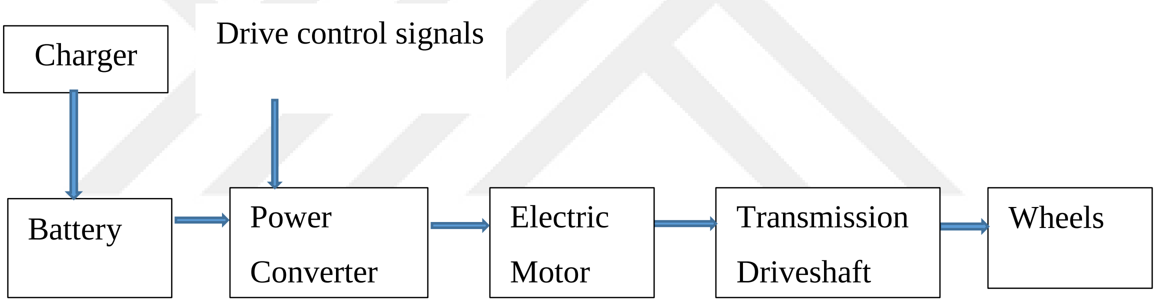


Figure 4.1. *Electrical vehicle components*

The features required for an electric motor in a battery-powered electric vehicle are listed below.

- Maneuvers such as start-stop, acceleration and deceleration during driving cause a temperature increase on the electric motor to create thermal stress. Water cooling system is needed to eliminate this pressure.
- It must have a Continuous / highest power ratio that can meet the requirement in the event of instantaneous acceleration. This ratio is approximately 1.5-2.
- There is a need for a wide constant power range, which is generally expected to be 1: 3 or 1: 4, allowing travel at high speeds.

- High efficiency, wide range of speed and torque ranges that allow the use of battery energy to reach a longer range is another required feature.
- The engine is expected to have a good geometric structure with the smallest size and weight.
- It should meet the expectation of low cost, high performance and confidence.

When all the required parameters are examined, it is easily understood that even by optimizing the electric motor, a significant improvement can be made on the electric vehicle. Therefore, in this thesis, it is tried to present the minimum size electric motor with the most suitable features to the person with the optimization of the demanded power only.

In addition, the data and attributes used in the driver classification process in the thesis study are in parallel with the steps required in the design of electric vehicles. Therefore, the engine optimization performed in line with the classification has an effect on the whole vehicle. Other components of this recommended vehicle are also compatible with the driver.

- ✓ The frequency of the use of gas-brake pedals, which are also taken into account in the classification of drivers, will also be used for the solution of the acceleration-deceleration frequency problem. Feature 1 and feature 2 is directly linked to pedal operation
- ✓ Angular velocity information were used to create feature 3 during the classification stage. This shows that the battery-motor modeling/optimization according to the class of drivers is the second optimization parameter that needs to be realized.

4.2.1. Determination of the needed power of an electric motor on the basis of acceleration time of the electric car

In electric car designs, only the maximum speed is taken into account when calculating the power required by the electric motor, but this does not reveal the motor's ability to accelerate at a given speed (Evtimov and Ivanov, 2016; Juraj, 2015; Besselink, 2010). Therefore, there is no guarantee that maximum speed can be achieved with the desired acceleration during traffic flow. Contrary to this approach, taking into account the other auxiliary systems that use energy in the electric vehicle, the power required is actually significantly higher than the calculated one (Evtimov and Ivanov, 2016; Juraj, 2015; Chen, 2015; Larminie and Lowry, 2003). Some studies in the literature related to the selection of the electric vehicle engine acceleration intensity can not be taken into account. However, the acceleration intensity plays an important role in the calculation of the electric vehicle draft (Ehsani et al., 2010; Besselink, 2010).

Where a more powerful electric motor is preferred, the maximum speed is determined by the maximum rotational speed of the electric motor (Evtimov and Ivanov, 2016; Ehsani et al., 2010; Besselink, 2010). The problem of determining the power of the electric motor applies to hybrid and converted vehicles in the same manner as electric vehicles (Chen, 2015; Marinescu, 2009; Marinescu, 2012). This problem is solved by using complex modeling and simulation tools (Juraj, 2015; Schaltz, 2011). In this thesis, the power required by the electric motor is calculated by a method based on acceleration time.

The required power equation is expressed in Eq. (4.1), depending on the acceleration time of the electric vehicle at a given speed (Sapundzhiev et al., 2017).

$$t_a = \int_0^{V_b} \frac{\frac{G}{g}\delta_a}{\frac{P}{V_b} - Gf_f - \frac{1}{2}k_e S V_b^2} dV + \int_{V_b}^{V_f} \frac{\frac{G}{g}\delta_a}{\frac{P}{V_f} - Gf_f - \frac{1}{2}k_e S V_f^2} dV \tag{4.1}$$

V_f-final speed(km/h),

V_b-base speed(km/h),

f_f– the rolling resistance coefficient;

δ_a – the coefficient of influence of the rotating masses of the car;

g – the Earth acceleration.

G– the weight of the electric car(kN);

k_e– the coefficient of air resistance of the electric car;

S– the front area of the electric car(m^2);

P – the power of the electric motor(kW);

The demanded power consists of two parts as seen in the equation. The first portion consists of the range where the velocity takes the value 0-V_b, while the second portion is defined by the velocity range V_b-V_f. Torque and power curves versus speed changes in these ranges is also given in Figure 4.2.

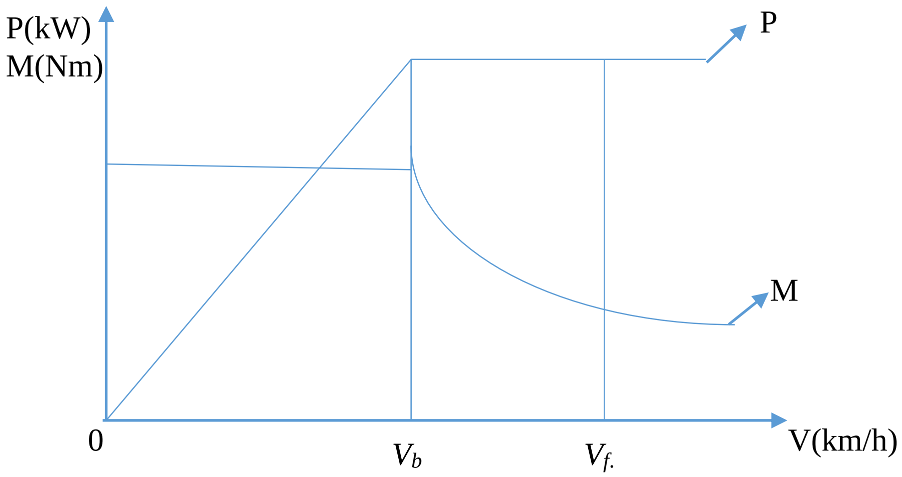


Figure 4.2. *The electric motor torque M and power P in function of car speed V*

Assuming that the power for overcome the rolling P_f and air resistances P_B are not dependent on the curve of the motor torque but only on the speed of motion, then P_f and P_B can be presented separately and after integration are expressed by the Eq. (4.2) and Eq. (4.3), respectively.

$$P_f = \frac{2}{3} G f_f V_f \tag{4.2}$$

$$P_B = \frac{1}{5} k_e S {V_f}^2 \tag{4.3}$$

2/3 and 1/5 coefficients are the values obtained as a result of the integration. When these expressions are written instead of Eq. (4.1), the acceleration time is obtained as Eq. (4.4).

$$t_a = \frac{\delta_a G}{2 g P_a} \left({V_f}^2 + {V_b}^2\right) \tag{4.4}$$

After remaking of Eq. (4.4), the average power needed during the acceleration time of the electric vehicle is equal to Eq. (4.5).

$$P_a = \frac{\delta_a G}{2 g t_a} \left({V_f}^2 + {V_b}^2\right) \tag{4.5}$$

The demand power is obtained as the Eq. (4.6) by replacing Eq. (4.2), Eq. (4.3) and Eq. (4.5) in Eq. (4.1).

$$P = \frac{\delta_a G}{2 g t_a} \left({V_f}^2 + {V_b}^2\right) + \frac{2}{3} G f_f V_f \frac{1}{5} k_e S {V_f}^2 \tag{4.6}$$

4.2. Optimization

The optimization is to obtain the minimum and (or) maximum value (s) of the function that mathematically expresses one or more objectives. Optimization problems can be single-objective or have multiple objectives and can be divided into "single-objective optimization" and "multi- objective optimization" problems according to the number of objectives. The number of objectives is equal to the size of the objective space. Therefore, in a two- objective problem, the aim space is two-dimensional. In any n-objective problem, the numerical values corresponding to the objective values are displayed in the n-dimensional objective space. The variables that affect the objective value independent of the number of objectives, in other words the different variables used in the objective functions are called decision variables, and similarly the number of decision variables is equal to the size of the decision space. Decision variables are the solution of the optimization problem. Decision variables form the solution (decision vector). The objective value of this solution is the value of the function to be minimized (or maximized). For single-objective optimization problems, the solution is a single value because the objective space is unidimensional, and for the minimization problem it is the decision vector that gives the smallest objective value that can be obtained within the specified limits. Of all possible solution vectors, the smallest decision vector is called "optimal solution" or "optimum". However, since a different objective value is generated against each decision vector in multi-objective optimization problems, the superiority of the solutions over each other is determined by considering each objective value. In other words, a single decision vector, n objective values are generated for a n-objective problem. Therefore, unlike single objective optimization problems, multi-objective optimization problem solving is not a single decision vector but a set of vectors. Similarly, the optimal solution is not a single vector but a set of vectors, which means that there cannot be a vector that produces a smaller objective value (for the minimization problem) than the solutions within this set of vectors. Any solution within this cluster is chosen by the decision maker, considering which purpose is important. There are multiple conflicting objectives for an optimization problem that may or may not be encountered in real life. These problems can be solved with the help of single-purpose optimization algorithms by reducing the multi-purpose problem to one purpose or by using algorithms developed for solving multi-purpose optimization problems.

Purpose values are applied to linear or nonlinear functions to make multi-objective optimization problems single-objective. Semantically, this process is the process of finding the solution with the desired properties by weighting the objectives before starting the algorithm instead of selecting one of the solutions produced by the multiobjective optimization algorithm after the algorithm ends. The common feature of the oldest preferred methods for solving single-objective and multi-objective optimization problems is the use of derivative of objective values. Numerical derivatives are obtained for the problems where analytical derivation is difficult. What is common in these methods is the numerical or analytical process of the derivation and the effort to solve a single decision vector (solution candidate) in the decision space at each step. These methods can be used with a single decision vector for multi-objective optimization problem solving or with multiple decision vectors.

Disadvantages of these methods are;

a) cannot search the decision space effectively because they use single point,
b) lack of effective exchange of information between points (population-based) if they use multiple points,
c) distribution problems in objective space and
d) nonconvergence to solution or slowness in convergence.

For this reason, heuristic methods (optimization algorithms that mimic natural phenomena with mathematical equations and connections) are preferred due to population-based, stochastic (random, random) distribution of solutions, faster convergence and independent of the properties of the problem (Altınöz, 2015).

Simply, the single-purpose optimization problem can be defined as given in Eq. (4.7). In this thesis, only minimization problem is investigated. However, any minimization problem may be converted into a maximization problem with *f(x)= - min(-f(x))* formula.

$$\min_{X} f(x) \tag{4.7}$$
$$g_i(x) \leq 0, i = 1, \dots, p$$
$$h_j(x) = 0, j = 1, \dots, m$$
$$x_k^L \leq x_k \leq x_k^U, k = 1, \dots, n$$

In Eq. (4.6), $f(x): R^n \rightarrow R$ is called as the objective function. The function of g(x) and h(x) are constraints, x^L and x^U are the minimum and maximum values of the *x* decision vector. These vectors are the limits of the search space ($x \in \Omega \subset R^n$). In single-objective optimization problems, it is aimed to find n-dimensional decision vector which minimizes/maximizes the given/defined objective function. The objective function maps the n-dimensional decision variable to the one-dimensional objective value. For any objective function, $f: \Omega \subseteq R^n \to R$ (Ω feasible region) optimal solution vector (x*) is a vector that produces a smaller objective value than all vectors in the definition space $\forall x \in \Omega$: f (x*) ≤ f (x).

The multi-objective optimization problem (MOOP) is as defined in Eq. (4.8). As can be seen from the equation, the number of limitations and objective functions is more than one. Although the number of objective functions must be more than one, there is no such constraint for ($F(x)=\{f_1(x),f_2(x),\ldots,f_l(x)\}$) constraint functions.

$$\begin{gathered} \min_X F(x) \\ G_i(x) \le 0, i = 1, \ldots, p \\ H_j(x) = 0, j = 1, \ldots, m \\ x_k^L \le x_k \le x_k^U, k = 1, \ldots, n \end{gathered} \tag{4.8}$$

In MOOP problems, the space in which the decision vector is defined, is called the search space or the decision space. Any point in the decision space constitutes the solution candidate. Mathematical expressions which map the solution candidate from definition space to purpose space are objective functions. Figure 4.3 shows the mapping between two spaces. In this way, two cases are emphasized. One of them is the definition space, which corresponds to the shape formed by the decision space boundaries, and it also shows an uncertain area. This is important in defining convex and non-convex problems. Although the definition range of the decision space is specific in the algorithm, the objective space limits can be determined by additional codes to be included in the desired algorithm.

The other case; a linear connection between the solution in the objective space (“the point”) corresponding to the solution candidate in the decision space cannot be mentioned. Although in many of the test problems the connection between decision space and objective space can be obtained using mathematical and statistical methods, such a correlation may not exist and/or the connection cannot be expressed mathematically correctly.

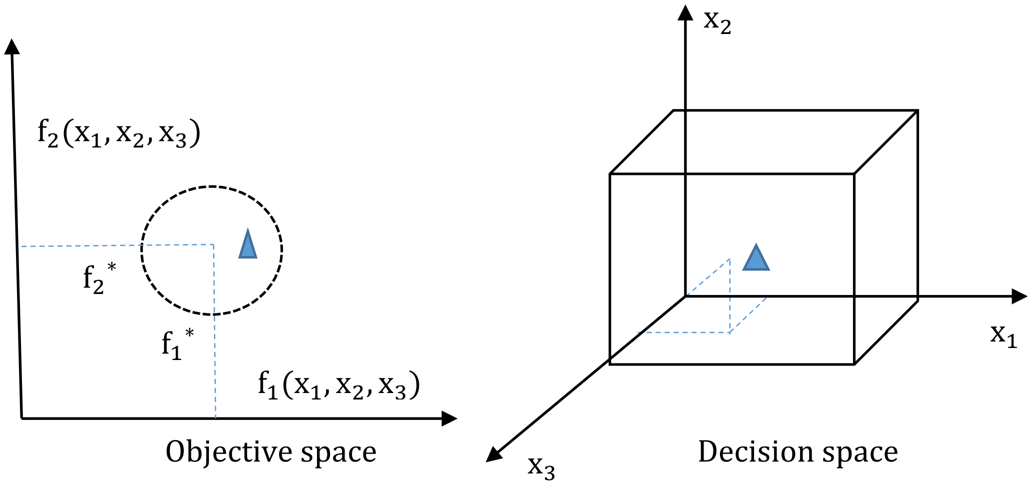


Figure 4.3. *Relationship between decision and objective space (Altınöz, 2015)*

Unlike single-purpose optimization problems, each objective value needs to be taken into consideration in determining which of the solutions is the best solution candidate in multiobjective optimization problems. In single-purpose optimization problems, the solution that gives smaller objective value is the best among the two solutions. Similarly, when comparing different algorithms, the algorithm that produces the smaller objective value is better. However, since the multiobjective optimization has more than one objective value, a separate definition should be made. First, Pareto called this definition "dominance".

Definition 1: Any $x^{(1)}$ solution ($x^{(1)}=\{x_1^{(1)}, x_2^{(1)}, \ldots, x_k^{(1)}\}$) defined in decision space suppresses $x^{(2)}$ solution candidate ($x^{(2)}=\{x_1^{(2)}, x_2^{(2)}, \ldots, x_k^{(2)}\}$) in the same space. It is shown as ($x^{(1)} \leq x^{(2)}$).

1. For all the objective values, $x^{(1)}$ must have bigger values than $x^{(2)}$ $f_i(x^{(1)}) \leq f_i(x^{(2)}), i = 1,2, \ldots, l$.
2. At least for one objective value, $x^{(1)}$ must be smaller than $x^{(2)}$ $f_i(x^{(1)}) < f_i(x^{(2)}), i \in \{1,2, \ldots, l\}$.

Figure 4.4 is given as an example to explain the definition of dominance. Two objective functions and three solution candidates are given in the figure. From these three vectors, it can be seen that the C vector produces the best value for each objective function (C≤ A), (C≤ B). Other vectors appear to give the best results for each objective value.

Although the second objective value of vector A is better than the B vector, it appears that the first objective function value of vector B is better than the vector A. Therefore, the dominance of vector A and B relative to each other cannot be mentioned. Among the solution candidates, a set of solutions that cannot be suppressed by any solution can be obtained. This set is the solution set generated by the MOOP algorithm, and the decision maker is asked to select the solution from this set.

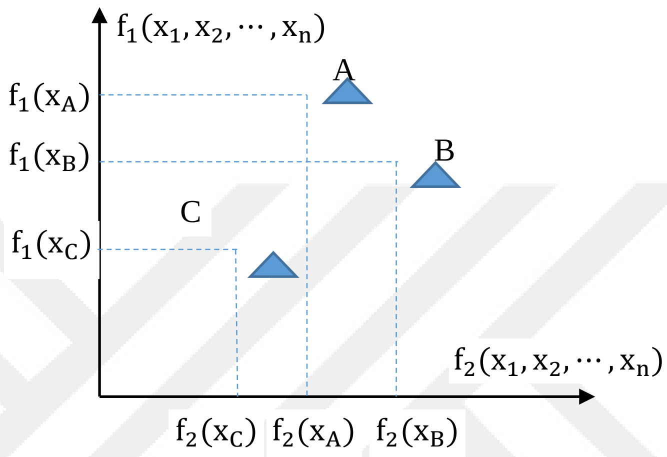


Figure 4.4. *Comparison of three objective vectors defined in objective space (Altınöz, 2015)*

Definition 2: Of all the P solution candidates, the P' solution candidate, which is not imprinted by other solutions, forms the unprinted solution set. The concept of a non-printing solution set can be expanded for the entire definition space. In this case, the set of non-reprinted solutions to be obtained from all possible solution candidates within the definition space represents the optimum set (i.e. Pareto-optimum) and as defined below.

Definition 3: The set obtained from the whole Ω definition space is the Pareto set. The shape of this set in the aim space is called the Pareto cluster. Theoretically, the Pareto front consists of an infinite number of solutions. For this reason, the actual Pareto cluster is not achieved in applications and only "approximately" the Pareto cluster is represented by a finite number of solutions. Figure 4.5 shows an example Pareto cluster in two-dimensional objective space. The Pareto cluster can have different shapes in different problems. The most common form is convex. The definition of convex is given below. In a convex multiobjective optimization problem, the Pareto front is also convex. But the opposite is not always the case. A problem with the convex Pareto front does not have to be convex.

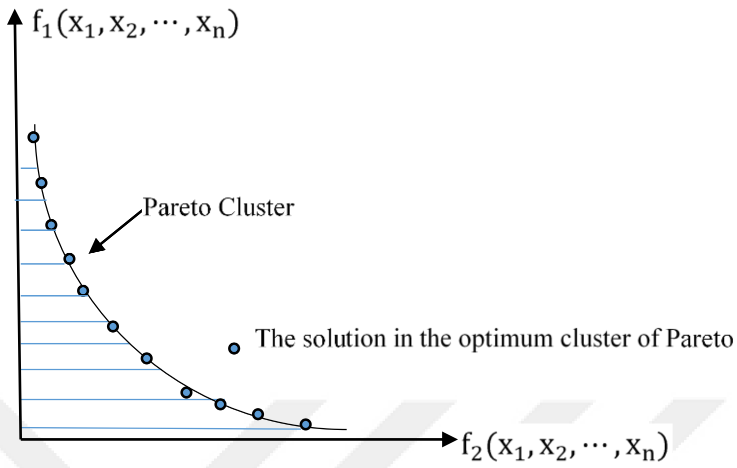


Figure 4.5. *Pareto cluster (Altınöz, 2015)*

Definition 4: In order for $f: R^n \rightarrow R$ function to be a convex function, any two pairs of solutions, $x^{(1)}, x^{(2)} \in R^n$ that can be selected must satisfy the following condition in Eq. (4.9).

$$f\left(\lambda x^{(1)} + (1-\lambda)x^{(2)}\right) \leq \lambda f\left(x^{(1)}\right) + (1-\lambda)f(x^{(2)}) \tag{4.9}$$

Definition 5: In case all purpose functions and definition space for an multiobjective optimization problem is convex, the multiobjective optimization problem is called convex.

Pareto provides the best possible set of multionjective optimization problem solutions. Similarly, the objective vectors that give the boundaries of Pareto optimum solutions in each dimension individually are called ideal vectors and rare vectors. The ideal vector $(f_i\left(x^{(0)}\right) = \sup(\cup_{x\in\Omega} opt f_i(x)), supremum)$ is the vector that holds the optimum value of each objective in the multiobjective optimization problem. Rare objective vector $(f_i\left(x^{(0)}\right) = \inf(\cup_{x\in\Omega} opt f_i(x)), infimum)$ gives each vector the minimum value of each objective dimension of an objective value. These values give both the boundaries of the solution space and the Pareto front end points. Ideal and rare points graphically as summarized in Figure 4.6.

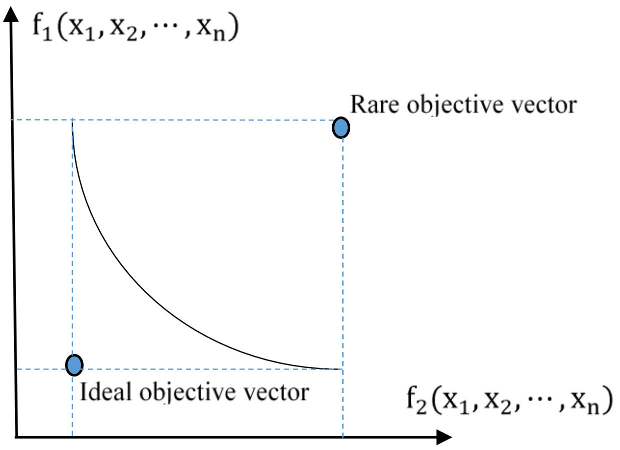


Figure 4.6. *Representation of ideal and rare purpose vectors on the Pareto cluster (Altınöz, 2015)*

4.3. Genetic Algorithm

Genetic Algorithms (GA) is an heuristic optimization technique used to find exact or approximate results for a search or optimization problem. Heredity in evolutionary biology was inspired by techniques such as mutation, selection and crossover (Kevran, 2009).

GA, whose basic principles were introduced by John Holland in the 1970s, has been successful in many types of problems (Mitchell, 1998). GA can easily be applied to complex problems consisting of multidimensional functions, where the search space is too large, where constraints are unclear or not fully defined, and the number of variables is too high, and meaningful results can be achieved. Genetic algorithms can produce reasonable results for short periods of time as a result of the tendency to stay away from values that may give bad results or to try out better values instead of searching the whole space in search space. Other population-based algorithms have similar applications, and the mutation operator has a low tendency to reach local minimum values. GA has a wide range of applications since it can be applied in both discrete and continuous functions. It is a common optimization method because it has been applied in many problem areas and many sub-methods have been developed for better performance of the algorithm.

GA is a population-based optimization method. Values, which are expressed by names such as chromosomes, genotypes, genes, which are an abstract definition of candidate solutions that make up the population, turn into solution candidates that represent better results as a result of various evolutionary-based processes. This process is continued until an acceptable conformity value is reached or criteria such as a predetermined process time, number of generations are met. Usually candidate solutions are expressed as strings of 0 and 1, but this is not a general rule and may vary according to the type of problem.

GA consists essentially of a population of candidate solutions and a suitability function. Candidate solutions (chromosomes) are strings that hold variables with discrete or continuous values of the solution they represent. The suitability function is a function that measures the quality of candidate solutions.

4.3.1. Initial population

In GA, the initial population is usually composed of random candidate solutions. There is no ideal value for population size. This value can range from 10-20 to 100s. However, it is considered that keeping the population size too high has no effect on the solution time of the problem or the goodness of the obtained value. In this regard, values of 20-50 are generally preferred for the initial population. The selection of optimization parameters, such as population size, is in a sense a separate optimization issue, and generally, different optimization parameter values are tried on different types of problems and good results are used.

4.3.2. Fitness value

Calculation of the fitness value in GA is done by subjecting each chromosome to the fitness function and obtaining the result. This process corresponds to the process of selecting "who is better or who is worse" in the evolutionary process. This is a mandatory procedure for GA, and GA cannot be applied to problem types where the suitability function cannot be determined.

On the other hand, the suitability function is only 0-1, yes-no, true-false etc. it also means that conformity function is not used. Compatibility functions can be costly functions in some problem types. In this case, it is advisable not to use GA to solve the problem, to solve the problem in a more restricted search space, or to use approximative functions with certain assumptions as the suitability function to be used.

4.3.3. Crossover

After all chromosomes that make up the population have been subjected to the conformity function, new chromosomes are formed by crossing the chromosomes with relatively better chromosomes, rather than with relatively poor chromosomes, in order to form new and better chromosomes. The cross-over performs the function of transferring the accumulation in the chromosomes of good value to the new chromosomes. Crossover is usually not performed on all chromosomes, but if applied, elitism is often used to prevent loss of optimal chromosome values.

The crossover process is usually formed by genes from two parent chromosomes, and genes up to a point to be determined at the starting point of the chromosome are taken from the first parent chromosome and the genes after that point are taken from the second parent chromosome. However, multi-parent and multi-point crosses can also be used.

Various selection strategies are used for crossover. Two of these are the Roulette Wheel Method and Tournament Method.

- **Roulette wheel method:** The basic logic of the Roulette Wheel selection strategy; The probability that chromosomes with high conformity values can be selected as parent chromosomes is kept higher than chromosomes with relatively low conformity values. The suitability values of all chromosomes are summed and the suitability value of each chromosome is calculated as a percentage value. In the next step, chromosomes with two random values to be selected between 1 and 100 are selected as parent chromosomes. With this application, the chance of selecting the genes to be created from child chromosomes to be created from parent chromosomes with high conformity values is increased. However, chromosomes that have small suitability values, even with small percentages, have the chance to be selected as parent chromosomes (http-6).
- **Tournament method:** In the Tournament Method selection strategy, the best chromosomes are chosen as parent among the k (tournament size) number of chromosomes randomly selected from the population. If the tournament size is kept high, the chance of selecting chromosomes with low fitness values will be reduced (Miller and Goldberg, 1995).

4.3.4. Mutation

The mutation process increases the diversity of chromosomes within the population, thus creating possible new solution candidates (chromosomes), thus avoiding the local minimum. In the mutation process after the cross-over, the values of the chromosomes are randomly changed within a mutation rate to be determined. The mutation rate is usually a coefficient that is kept as low as 0.5% to 5%.

The mutation process may vary depending on the structure of the chromosome. For example, if only chromosomes encoded with values 0 and 1, values 1 can be made 0, values 0 can be made 1. Similarly, if chromosomes are coded using real numbers, addition or subtraction can be performed with a random value to be determined within the mutation rate to be determined.

4.3.5. Elitism

Preservation of the best value (s) obtained within the population in GA is a widely used method. This can be done by keeping the chromosome ratio to be crossed low or keeping the best value in a separate variable if the whole population is going to be crossed and mutated.

4.3.6. Variable mutation rate

The low rate of mutation means that new solution candidates should be searched in the search space in close proximity to existing solutions. However, in some cases, it is considered that increasing the mutation rate may help to improve the compliance function if the improvement function of the population cannot be achieved for a long time.

As another application, following the formation of the population, keeping the mutation rate at very high values, making a near random search in the search space; it can be applied by decreasing the mutation rate with the following generations, and to search for better values in locations close to the obtained good values. In fact, in simulated annealing, a similar heuristic optimization method, while the energy (temperature) levels of the atoms were high at first (this corresponds to a high mutation rate in GA), the temperature is lowered in the following stages. However, the variable mutation rate method should be used to keep the population size high and elitism method should be used. In this way, it is evaluated that the best values determined at different locations of the search space will be stored and searched in a wider region.

4.3.7. Prevention of homogenization of population

The heterogeneity of the population in GA is an important issue in terms of creating new solution candidates and thus increasing the possibility of finding a better solution. In this respect, chromosomes in the population should be prevented from being exact copies of each other. In cases where this application is not performed and the mutation rate is kept low, the accumulation of chromosomes in a restricted solution region of the search space or even in the same location may not be prevented.

As a solution, two or more identical chromosomes, if any, can be identified by replacing these chromosomes with completely random values or the chromosomes can be included in the next generation. However, if the population is very homogenized and the mutation rate is kept low, crossover may not work.

4.4. Multi-Objective Genetic Algorithm

Real world problems are complex, and multiple goals need to be achieved for a good solution. Many projects offer solutions based on a single function. This simple approach is not very effective in most cases (Kaya and Güngör, 2007). First, the objectives can often conflict with each other. Second, the objectives may often not be appropriate to the quality of the candidate solution and may vary. In multi-purpose GAs, both of these situations are minimized. The natural and evolutionary structure of the genetic algorithm is also suitable for multi-purpose structure. Pareto's optimal solution is well suited to the nature of multi-purpose GA (Goldberg, 1989). Goldberg's selection algorithm (2002) uses the multipurpose evolutionary algorithm proposed in (Deb, 2001; Coello et al., 2002).

In multi-purpose genetic algorithms, more than one goal is looked at at the same time. So there is not a single optimal solution. A set of solutions can be selected by making a choice between the objectives. With this method, the user can select one of the possible solutions for the specific problem. Thus, the user will have the opportunity to select a set of solutions by examining the high quality solutions and making a choice between the objectives. This method is better than forcing the user into a single set of solutions.

The reasons why multi-objective GAs are preferred are:

1. Genetic algorithms are powerful algorithms because of the large search space.

2. . Genetic algorithms are a global search method and communicate with objects more easily than greedy search methods.

3. Genetic algorithms work with a set of candidate solutions to solve multi-objective problems.

An example for multiobjective problem is shown in Figure 4.7.

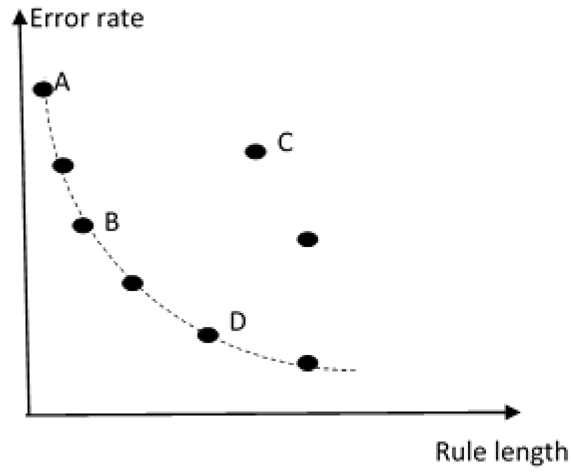


Figure 4.7. *An example for multiobjective problem(Kaya and Güngör, 2007)*

In Figure (4.7), solution A has a low rule length but a high error rate, solution D has a low error rate but a high rule length. Since both objectives are important; Solution A is better than D, or vice versa. On the other hand, solution C is worse than D. In this study, a three-purpose problem is considered. The aim is to find a small number of "IF-IF" sets of fuzzy rules that contain a small number of objects with high classification performance. This process is to maximize the classification accuracy rate, to minimize the number of selected rules and to minimize the total rule length.

4.5. A Novel Application: Multi-Objetive GA to optimize Electrical Vehicle Power using Driver Behaviour Data

The acceleration times of the driving classes were determined from the driving data obtained in the previous periods. These values are defined as the time to reach the speed value determined for each class. In general, this value is considered to be 100km/h, and since the work is performed on campus for the most part, most of the drivers do not reach this speed, so a common speed value is determined for all drivers. This speed value is selected as the maximum speed that the calmest driver has reached once. The expected speed value for the study is 40 km/h. The times that the drivers have reached this value are given in Table 4.1.

Table 4.1. *Acceleration time of drivers*

Driver class		Acceleration time(s)	Mean acceleration time(s)
Conservative	1st Drive	13	42.3
	2nd Drive	40	
	3rd Drive	49	
	4th Drive	40	
	5th Drive	49	
	6th Drive	47	
	7th Drive	45	
	8th Drive	41	
	9th Drive	71	
	10th Drive	34	
	11th Drive	34	
	12th Drive	41	
	13th Drive	38	
	14th Drive	42	
	15th Drive	51	
Moderate	1st Drive	11	16
	2nd Drive	47	
	3rd Drive	46	
	4th Drive	11	
	5th Drive	13	
	6th Drive	11	
	7th Drive	7	
	8th Drive	11	
	9th Drive	16	
	10th Drive	13	
	11th Drive	14	
Aggressive	1st Drive	10	9.72
	2nd Drive	8	
	3rd Drive	8	
	4th Drive	7	
	5th Drive	3	
	6th Drive	9	
	7th Drive	15	
	8th Drive	13	
	9th Drive	13	
	10th Drive	9	
	11th Drive	13	
	12th Drive	9	
	13th Drive	8	

These values are used in the following power demand function (Eq.(4.10)) to create the first objective function to be optimized for the power demanded for each class. Optimization variables for this equation in the literature are determined as V_f and V_b. Therefore, in the stage of defining the genetic algorithm optimization problem, V_f and $V_b$values appear as genes.

These values determine the vehicle's engine selection. Multi-objective genetic algorithm was chosen as the optimization method. Therefore, a second objective function is determined as Eq. (4.11) with respect to the vehicle's speed factor.

$$P = \frac{\delta_a G}{2t_a g}\left(V_f^2 + V_b^2\right) + \frac{2}{3} G f_f V_f + \frac{1}{5} k_e S V_f^2 \tag{4.10}$$

$$SF = \frac{V_b}{V_f} \tag{4.11}$$

Lower and upper limits are added as constraints for V_f and V_b speed values determined as optimization variable. The maximum speed values of the drives have been defined as the average speed values for the $V_f$variable and the constraints for the V_b speed variable.

Maximum and average speed values of all drivers are given in Table 4.2.

Table 4.2. *Maximum and mean speed values*

Driver class		Max Velocity(km/h)	Mean Velocity(km/h)
Conservative	1st Drive	54	32.4
	2nd Drive	57	32.4
	3rd Drive	54	32.4
	4th Drive	54	32.4
	5th Drive	50	28.8
	6th Drive	48	28.8
	7th Drive	54	32.4
	8th Drive	56	32.4
	9th Drive	49	25,2
	10th Drive	55	32.4
	11th Drive	61	36
	12th Drive	60	32.4
	13th Drive	54	32.4
	14th Drive	53	32.4
	15th Drive	65	32.4
Moderate	1st Drive	65	36
	2nd Drive	55	28.8
	3rd Drive	60	32.4
	4th Drive	70	39.6
	5th Drive	56	39.6
	6th Drive	63	32.4
	7th Drive	64	36
	8th Drive	65	36
	9th Drive	61	36
	10th Drive	64	36
	11th Drive	65	36
Aggressive	1st Drive	68	39.6
	2nd Drive	64	39.6
	3rd Drive	65	39.6
	4th Drive	86	50.4
	5th Drive	105	61.2
	6th Drive	79	39.6
	7th Drive	74	39.6
	8th Drive	75	36
	9th Drive	74	39.6
	10th Drive	70	57.6
	11th Drive	90	68.4
	12th Drive	95	39.6
	13th Drive	116	39.6

$$f_1(\boldsymbol{v}) = \frac{\delta_a G}{2t_a g}\left(V_f^2 + V_b^2\right) + \frac{2}{3}Gf_fV_f + \frac{1}{5}k_eSV_f^2$$

$$f_2(\boldsymbol{v}) = \frac{V_b}{V_f}$$

$$\min_{\boldsymbol{v}} f(\boldsymbol{v}) = (f_1(\boldsymbol{v}), f_2(\boldsymbol{v}))^T$$

$$subject\ to\ \boldsymbol{v} \in \boldsymbol{V} = \left\{ \boldsymbol{v} \in R^n \middle| V_{f_l} \leq V_f \leq V_{f_u}, V_{b_l} \leq V_b \leq V_{b_u} \right\}$$

The limit values V_{f_l}, V_{f_u}, V_{b_l} and V_{b_u} take different values for the three drive classes.

According to the values in the table, the constraints were determined for V_f and V_b variables belonging to three classes. These values are selected as the min and max values of the drive speed values in each class. Optimization constraints are given in Table 4.3.

Table 4.3. *Constraints of speed variables*

Driver Class	V_f		V_b	
	Lower Limit	**Upper Limit**	**Lower Limit**	**Upper Limit**
Conservative	50	61	25.2	36
Moderate	55	70	39.6	28.8
Aggressive	64	116	68.4	36

In the thesis, matlab program was used for optimization solution with genetic algorithm. The multiobjective GA function uses a controlled elitist genetic algorithm.

- The multi-objective genetic algorithm (gamultiobj) operates on a population using a number of operators applied to the population. The population consists of a series of points in the design space. The said program randomly generates the first population. The next generation is calculated by considering the non-dominant rank and the distance measure of individuals in the current generation.
- Population type is chosen as Double Vector because the individuals in the population are of double type.
- gamultiobj uses only the Tournament ('selectiontournament') selection function.
- The crossover process for the program used is as follows.

Intermediate ('crossoverintermediate'), the default crossover function when there are linear constraints, creates children by taking a weighted average of the parents. You can specify the weights by a single parameter, Ratio, which can be a scalar or a row vector of length Number of variables. The default is a vector of all 1's. The function creates the child from parent1 and parent2 using the following formula.

child = parent1 + rand * Ratio * (parent2 - parent1)

- The mutation process for the program used is as follows
  Adaptive Feasible ('mutationadaptfeasible'), the default mutation function when there are constraints, randomly generates directions that are adaptive with respect to the last successful or unsuccessful generation. The mutation chooses a direction and step length that satisfies bounds and linear constraints.
- The Pareto fraction has a default value of 0.35
- Population size:50

The Pareto solution set obtained as a result of optimization with genetic algorithm is given in Figure 4.8, Figure 4.9 and Figure 4.10 for aggressive, normal and quiet drives, respectively. All the solutions present the optimum solutions for the specified class.

Each point on the generated curve is obtained by optimization with genetic algorithm. These values are the optimum values of the electric motor characteristics that will appeal to all drivers in that class. Since there is no domination between the two objective functions, it is left to the driver to choose between the values indicated in the graph. The driver will be able to travel with the comfort of his choice without changing the driving behavior of a vehicle with an electric motor providing one of the optimum points on this curve. Rather than buying a vehicle with a speed limit that will not be used for the rest of his life, the driver is able to obtain both economic and environmental benefits by selecting a vehicle that meets his own demands. Instead of suggesting a direct type of motor, it was tried to reach the aim of meeting the wishes of all the drivers by offering the possible options to the driver's choice.

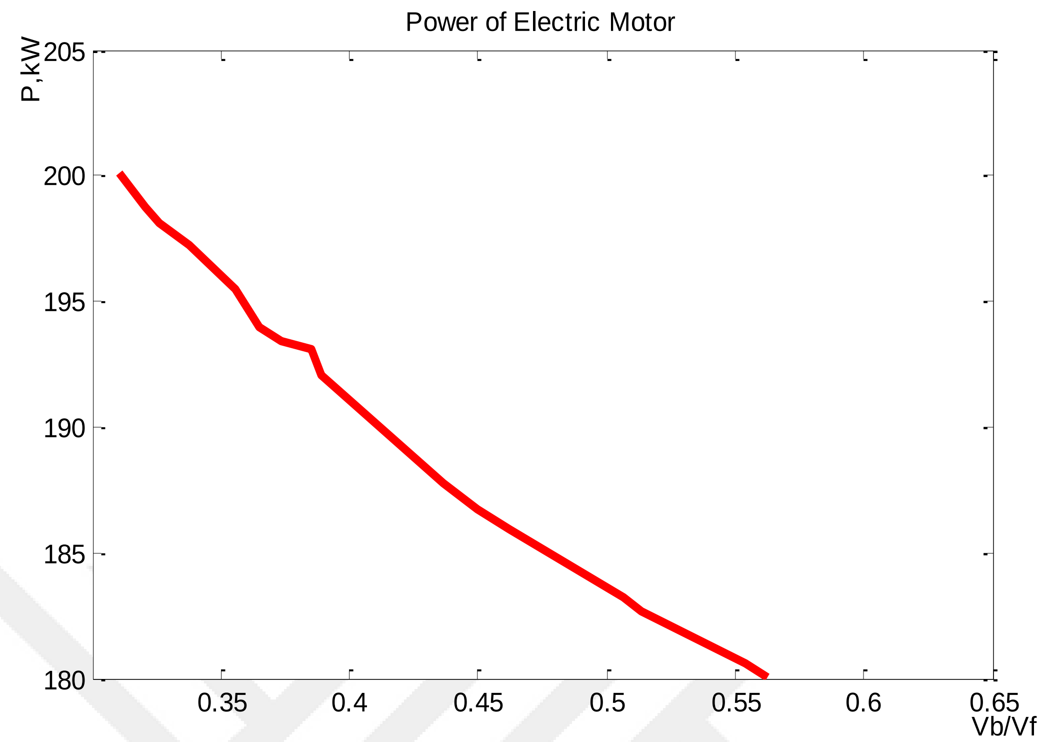


Figure 4.8. *Required power of the electric motor vs. the speed factor (Vb/Vf) for aggressive driver*

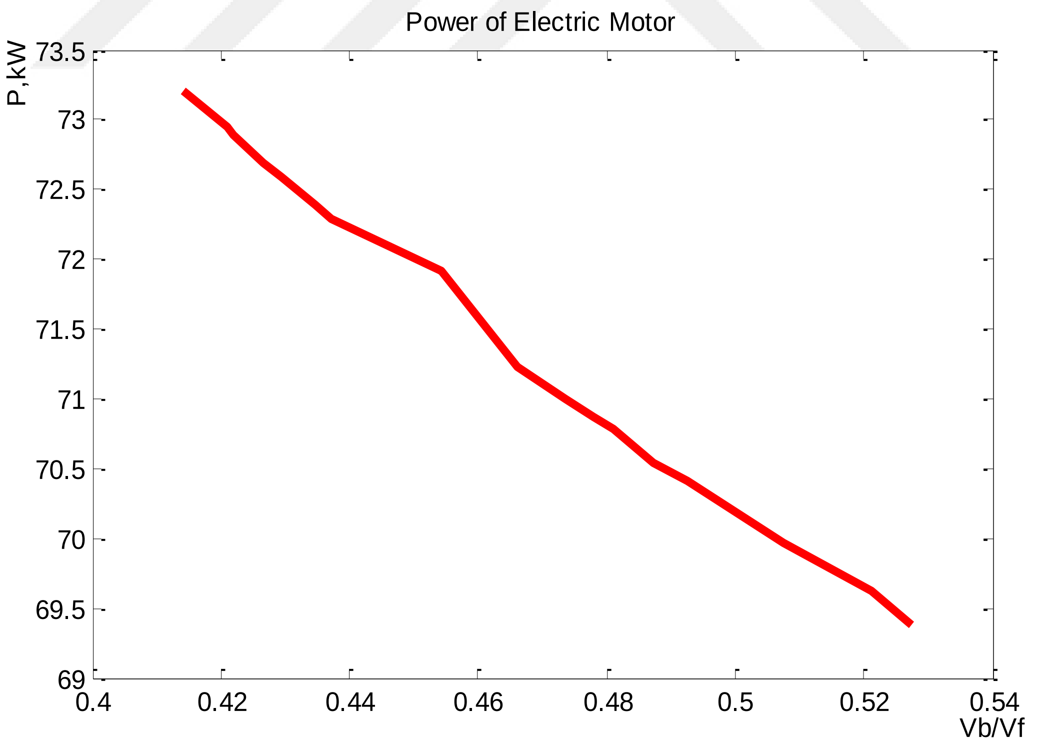


Figure 4.9. *Required power of the electric motor vs. the speed factor (Vb/Vf) for moderate driver*

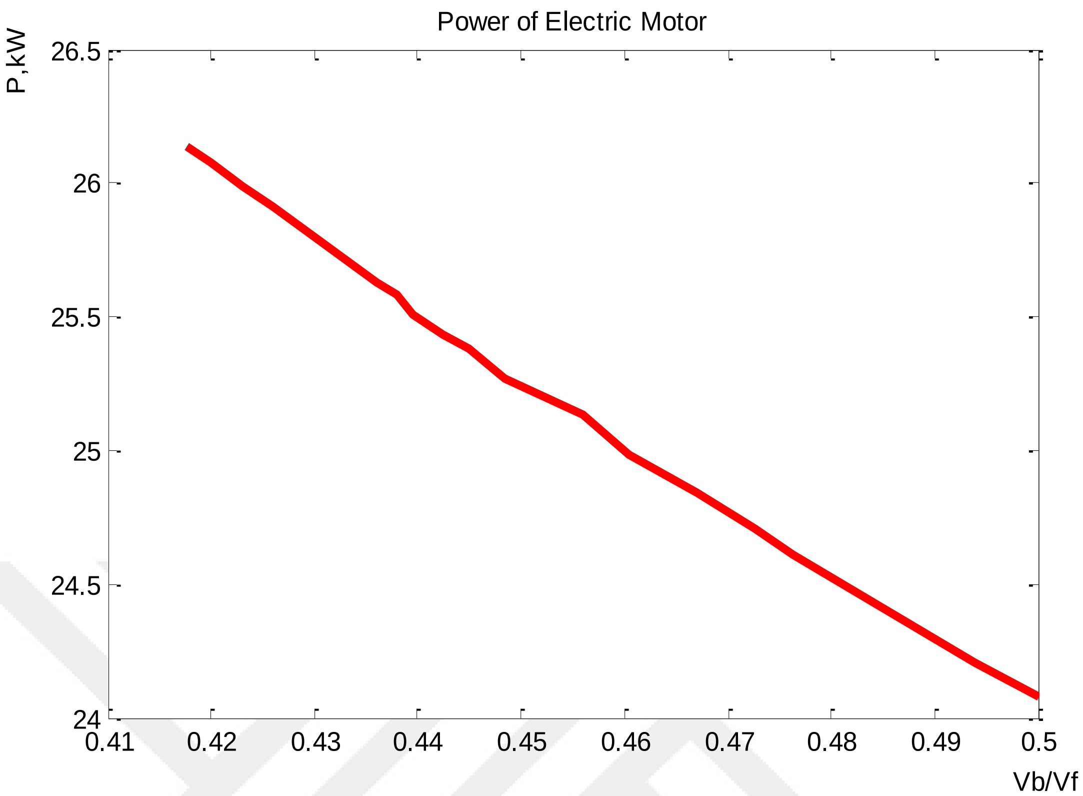


Figure 4.10. *Required power of the electric motor vs. the speed factor (Vb/Vf) for conservative driver*

The aim of this algorithm is to find the optimum electrical power of the motor. As a result of the optimization, 3 classes are founded as the following for the drivers. And Image 1-3 are the suitable examples for these classes of drivers from the automotive market.

25 kw – 34 hp –Conservative Drivers

65 kw- 88 hp – Moderate Drivers

185 kw – 248 hp – Aggressive Drivers

Image 4.1. *Electric vehicle 1(38 hp)*

Image 4.2. *Electric vehicle 2(95 hp)*

Image 4.3. *Electric vehicle 3(248 hp)*

For the vehicles which are an indispensable part of daily life, technologies are being developed to serve different purposes. The manufacturer's liability is not limited to the manufacture of the vehicle. Many issues such as energy consumption, fuel cost and greenhouse gas emissions are the working areas of manufacturers and scientists. As these issues have both material and environmental consequences, the technologies developed on these issues are vital for humanity. His research interests are engine efficiency, hybridization, vehicle weight and efficiency of powertrain. At this point, scientists resort to optimization methods. Most previous studies have focused on optimum power management and powertrain component sizing to achieve minimum vehicle energy use or achieve minimum life cycle costs and greenhouse gas emissions (Kim and Peng, 2007; Mohan et al., 2013; Shiau, 2010). In this thesis, minimum motor capacity is emphasized. The driving habits of the drivers are also taken into consideration when making the minimum engine recommendation. Vehicles with these engines provide all the comfort the user needs, while minimizing both the car weight and the required battery size and greenhouse gas emissions. Because of the different energy conversion and storage principles, the effects of light weighting on vehicle configuration and energy use are very different in conventional and electric drivetrain. A lighter vehicle uses less energy and requires a smaller powertrain and energy storage at a fixed range and performance, which reduces vehicle costs. The weight of a vehicle is defined by the following equation (4.12) (Hofer et al., 2014).

$$m_{veh} = m_{pt} + m_{es} + m_{gl} + m_{sup} \tag{4.12}$$

m_{veh}: Vehicle mass

m_{pt}: Power train mass

m_{es}: energy storage mass

m_{gl}: glider mass

m_{sup}:additional material mass

Hofer et al showed in their study the advantages to be achieved with the reduction of vehicle weight for electric vehicles and gasoline vehicles. With the decrease in weight, both production cost decreased and driving life was prolonged for both types of vehicles. The production values of the reference vehicle parts given for this study are given in the table below.

Table 4.4. *Baseline specific mass and cost of vehicle components(Hofer et al., 2014, pp. 284-295)*

	Unit	Mass	Unit	Cost	Source
Gasoline engine	[kg]	61	[$]	1000	(Brooker et al., 2013; National
	[kg/kW]	0.68	[$/kW]	7.4	Research Council., 2011)
Motor/controller	[kg]	22	[$]	500	(Graham, 2001; Duleep et al.,
	[kg/kW]	0.87	[$/kW]	28	2011)
Gasoline tank	[kg]	10	[$]	300	(National Research Council.,
	[kg/kWh]	0.14	[$/kWh]	0.6	2011)
Li-ion battery	[kg]	30	[$]	4000	(Gerssen-Gondelach and Faaij,
	[kg/kWh]	8.3	[$/kWh]	500	2012; Nelson, 2011)

Reducing vehicle weight has resulted in a production cost reduction of 24% for a 200km-range BEV vehicle and a 39% production cost reduction for a 400km-range vehicle. EPA reported in 2006 that 5 cycles should be used instead of 2 cycles when performing fuel consumption tests. However, the fuel performance of the vehicle used for different driving scenarios and conditions is demonstrated. This shows that driving habits directly change fuel consumption. In addition, while the biggest difference between electric vehicles and conventional vehicles is the greenhouse gas emission, this difference is the most aggressive and frequent stop-and-go braking gas usage. The Figure 4.11 clearly shows that the driving style affects all parts, including the service life of the vehicle (Karabasoglu and Michalek, 2013).

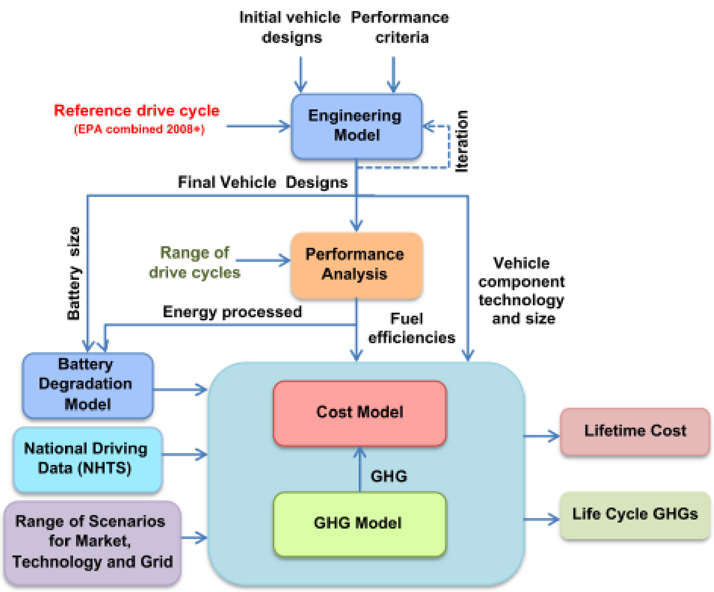


Figure 4.11. *Framework of vehicle life cycle benefit comparison for different driving patterns (Karabasoglu and Michalek, 2013, pp.449)*

Karabasoglu and Mchelik in his study have found for different vehicles in different driving modes. In the tests, comparisons were made for conventional vehicle (CV), hybrid electric vehicle (HEV), plug-in hybrid electric vehicle (PHEV) and battery electric vehicle (BEV). Vehicle specifications are shown in the table.

Table 4.5. *Vehicle specifications (Berry,2010; Karabasoglu and Michalek, 2013, pp. 450)*

Mass breakdown	**Units**	**HEV**	**PHEV20**	**PHEV40**	**PHEV60**	**BEV100**	**CV**
Vehicle glider/body mass	kg	815	815	815	815	815	815
Powertrain mass	kg	609	754	978	1212	1450	556
Vehicle curb mass	kg	1424	1569	1793	2027	2265	1371
Driver mass	kg	80	80	80	80	80	80
Total mass	kg	1504	1649	1873	2107	2345	1451
Engine							
Max. power	kW	73	73	73	73		110
Engine scale		1	1	1	1		1.5
Block mass	kg	108	108	108	108		166
Radiator mass	kg	6	6	6	6		6
Tank mass	kg	20	20	20	20		20
Fuel mass	kg	43	43	43	43		43
Total mass of engine block	kg	177	177	177	177		234
Motor							
Max. power	kW	60	78	88	98	120	
Motor scale		1.0	1.3	1.5	1.6	2.0	
Motor mass	kg	35	46	51	57	70	
Controller mass	kg	5	7	7	8	10	
Total mass of motor block	kg	40	52	59	65	80	
Motor 2							
Max. power	kW	30	30	30	30		
Motor mass	kg	20	20	20	20		
Controller mass	kg	5	5	5	5		
Total mass of motor 2	kg	25	25	25	25		
Battery							
Technology		NiMH	Li-ion	Li-ion	Li-ion	Li-ion	
Parallel cell array		1	5	10	14	25	
Number of cells in series		168	92	92	100	100	
Total # cells		168	460	920	1400	2500	
Cell capacity	Ah	7	6	6	6	6	
Nominal output voltage	V	1.2	3.6	3.6	3.6	3.6	
Output voltage	V	202	331	331	360	360	
Energy capacity	kWh	1.3	9.9	19.9	30.2	54.0	
Packaging factor		1.3	1.3	1.3	1.3	1.3	
SOC min	%	30	30	30	30	30	

Table 4.6. (Continue) Vehicle specifications (Berry,2010; Karabasoglu and Michalek, 2013, pp. 450)

SOC max	%	90	90	90	90	90	
SOC init	%	60	90/30	90/30	90/30	90/30	
SOC target	%	60	30	30	30	30	
Battery swing	%		0.6	0.6	0.6	0.6	
Mass of each cell	kg	0.4	0.4	0.4	0.4	0.4	
Total mass of battery block	kg	84	217	435	662	1182	22
Other Components							
Electrical accessories	kg	18	18	18	18	18	18
Exhaust mass	kg	30	30	30	30		30
Planetary gear mass/gear mass	kg	40	40	40	40		75
Mechanical accessories	kg	35	35	35	35		0
Wheel mass	kg	140	140	140	140	140	140
Final drive mass	kg	20	20	20	20	20	20
Torque coupling	kg					10	10
Alternator and controller	kg						7

The study was carried out for six different driving cycles, which varied according to parameters such as driving area, speed, acceleration. The first of the driving cycles is the Urban Dynamometer Driving Schedule (UDDS), which describes the journey of light-duty vehicles in city driving conditions at relatively lower speeds. The Highway Fuel Economy Test (HWFET), two driving cycles, refers to the driving performed under road driving conditions below the 60 mph speed limit, while the other driving cycle is the US06 cycle with high accelerations and engine loads. the LA92 cycle is the driving cycle in which aggressive driving is defined in urban driving conditions. The NYC cycle refers to low-speed urban driving that often has to be stopped and raised. The last driving cycle considered is the combined MPG cycle, calculated by EPA by weighting city and highway efficiency. Fuel consumption, cost, gas emission parameters were compared. The graphs in parallel with the results of this thesis are given below. In the Figure 4.11, 6 different driving costs are calculated for different types of vehicles. When calculating the cost, production, fuel used and electricity are all taken into consideration. Differences are observed in the production stage of the vehicles, but as the engine capacity increases for the vehicle with the same production cost, the consumption cost increases due to the required battery.

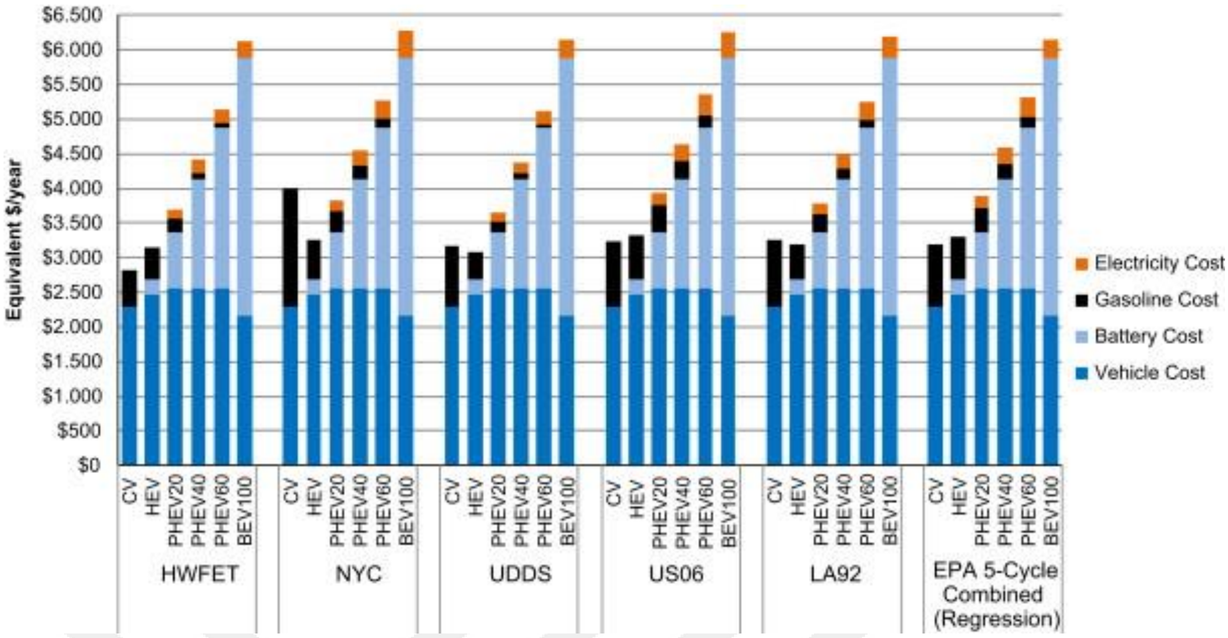


Figure 4.12. *NHTS averaged annualized cost breakdown per vehicle (base case) (Karabasoglu and Michalek, 2013)*

When the greenhouse gas emissions for all these driving modes are examined, the driving characteristics directly affect greenhouse gas emissions. The increase in the engine volume increases the emission of greenhouse gas from the electricity used. Already in the comparison between PHEV20-PHEV40-PHEV60 for all drives, oscillation is mostly produced by the PHEV60 test vehicle. Therefore, the electric vehicle with a low-capacity engine capable of providing the driver with sufficient comfort means less environmental pollution.

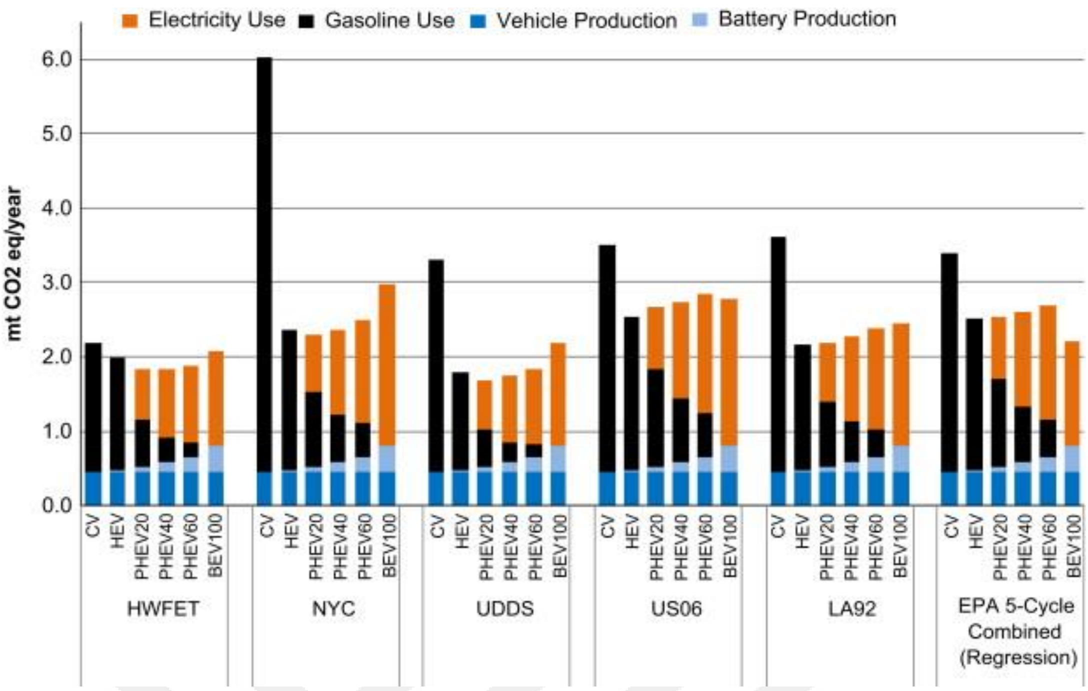


Figure 4.13. *NHTS averaged annual GHG emissions per vehicle (base case) (Karabasoglu and Michalek, 2013)*

5. CONCLUSION

The invention of the car is an adventure of discoveries dating back to the invention of the wheel in 3000 BC. The wheel, a steam-powered prototype, sketches by Leonardo da Vinci, the discovery of the first steam car inspired by them, the electric car and the internal combustion engine, goes back centuries. The invention of automobile has affected many subjects such as living spaces, needs, social life, economy, equality between men and women, wars and nutrition. The proliferation of automobiles has led to the construction of automobile roads, which has caused the geographical areas to change with huge bridges and tunnels. As automobile usage increases, greenhouse gas released to nature has damaged the atmosphere, causing global warming and the melting of glaciers at the poles, causing environmental pollution, climate change, and endangering species. Demand for the car has increased the value of gasoline, which has affected political balances around the world. As the production of automobiles increased, there was a need for women to work in automobile factories in Europe, the place of women in working life expanded and women struggling for equal rights gained the right to work today. Starting with the Ford Model T in the Ford Motor Company plants, mass production changed the industrial balance, and companies that reached the consciousness of producing more in less time pushed the button of the industrial revolution. As automobiles and motor vehicles became widespread, it became easier to move the products in the agricultural areas, the materials produced in the factories to different places, which means that the approach of equal food and nutrition luxury was approached.

The aim of the thesis is to classify the drivers into specific classes and to optimize the electric vehicle parameters for these classes and to provide a less harmful traffic to the environment while saving fuel, energy and costs. In this thesis, electric car was chosen among the car types and due to the importance of the subject, experimental studies were made on it. The experiments were carried out with vehicles with internal combustion engines commonly used now. The driving information obtained in this way ensures that there is no change in people's driving behavior and more realistic results. Drivers can be categorized in many ways: by gender (female driver-male driver), age (old driver-young driver), driving experience (experienced driver-inexperienced driver) etc. In this thesis, experiments have been conducted with male and female drivers who have driven vehicles of different age groups by considering these categories. Because it is thought that working with people in any category cannot provide complete accuracy in general conclusions.

The driving experience of 4 female and 9 male drivers, whose driving experience ranged from 3 to 20 years, was utilized in the 28-40 age range. The tests were carried out in a controlled manner, taking into account all the probabilities in traffic. The driving area includes all of the traffic elements such as pedestrian crossing, U-turn, lane change, curvature, pit, bump, pedestrian and vehicles on the road. In these drives, the data was provided by the smartphone application iDRIMS and the vehicle tracking device installed in the test vehicle. At this stage, two-stage recording was used to prove the data accuracy and eliminate noise effects. In addition to the data shared by the test tracker and the application, information that could reveal different features could be obtained separately. In accordance with the information that has not been used in this study, studies are continuing. An observer and the drivers participated in the rides carried out with the smartphone placed on the front panel of the test vehicle where the vehicle tracking device was mounted. This observer, taking into account traffic drivers, evaluated the drivers according to the criteria determined before driving and recorded how the driver showed the driving characteristics. She/He made the assignments according to the driver classes determined by the researcher and completed the test drives. The drivers were divided into three classes: conservative, moderate and aggressive. The number of classes has been selected considering the existing scientific studies in the literature. In addition, since the thesis study aims to make suggestions from among the vehicles in the sector, the number of classes that the driver can reach in the market is not considered and the number of classes is not selected more. Selecting less will also be inadequate for drivers to identify. When the drivers who participated in the study were observed, it was found that the number of classes was dull. The drivers were voluntarily participated in the tests without giving details about the purpose and content of the study before driving. The test vehicle is one of the most widely used vehicles in the world, the Toyota Corolla. By selecting the vehicle automatic gearbox, the effect of errors and pauses on the data is eliminated. Since some of the test drivers only use automatic gearboxes, the choice of the vehicle has been made in this direction since performing a test drive with a manual vehicle will affect the results. The tests were carried out shortly after the vehicle was purchased from the dealer, so there were no malfunctions or deformations in the vehicle components. As mentioned before, acceleration in the x, y and z directions was processed with three dimensional angular velocity and velocity relations. The studies in this field were examined and a selection was made to provide the most detailed examination among the data used.

Attributes are defined using this data. The acceleration of the driver in any direction while the attribute is defined can represent the driver's behavior at the points where the road structure such as bumps, pits encountered during the use of the vehicle changes, while also defining a change that occurs during lane change. Therefore, acceleration should be handled in three dimensions. However, the situation in which the driver performs this acceleration is not only related to this information but also to the angular acceleration information. Attributes were chosen in this direction. The drivers were classified with SVM and KNN algorithms by using 3 attributes initially determined. In order to prove the applicability of the classification during the classification made by using SVM algorithm, the obtained data were rotated with k-fold method and different training and test data tests were created. Among the 90 drives, only 1 drive is assigned to the wrong class by the algorithm. The driver in the calm class was assigned to the aggressive class, reducing the classification accuracy to 98.9%. In the KNN algorithm, which is applied as a second method, the neighborhood value where the highest accuracy is obtained was determined by changing the neighborhood values. Since the optimum k value changes for each problem and data, in the thesis study, k = 1, 3, 5, 7, 9, 11, the classification for 6 different k values was obtained as 85.55, 83.33, 93.33, 91.11, 90, 90, 74.44 respectively. These results showed that the percentage of classification accuracy does not show an increase or decrease parallel to the k value. In this study, the optimum k value was determined as 5 for the problem discussed. Just as the neighborhood value varies, the 4th feature is defined considering the contribution of increasing number of features to the subject of classification. 4. Markov chain was used to define the feature. At this stage, 20 different states were determined by considering both the velocity and angular acceleration distributions of the drivers and the transition probability matrices of all the drivers were formed. All cells in this matrix were examined one by one to determine which cells were dominant in which classes and which cells were significant. By creating a weight matrix that will reveal the effect of these identified cells, all probability transition matrices are multiplied by this matrix and a weighted average value is obtained for all drives. These mean values are added to SVM feature vector as the fourth element. In this way, classification procedures were renewed with the same steps. The increasing number of attributes caused the classification accuracy to decrease. The result of the 4-attribute SVM classification was obtained as 92.2% accuracy. In this way, the first stage of the thesis, the driver classification process, has been concluded with acceptable high accuracy.

When the previous scientific researches are examined, very high accuracy has been obtained by producing the features not included in any other study in this thesis. This accuracy has not previously been achieved in such a classification. Another advantage of the study was that the data obtained was directly used as raw data without any filtering and signal processing methods. With this stage, the thesis contributes scientifically to the literature.

For the second stage of the thesis, the tool parameters were analyzed and the component to be applied was determined. When literature studies are examined, instead of very complex equations and algorithms, a simple application point has been determined in which the effect of the change over the whole vehicle can be felt directly: electric motor. It is aimed to determine the power demanded by the driver from the vehicle and to select the appropriate engine for this power. First of all, in the first stage of the thesis, an arrangement was made for the drivers in each class to meet the demands of all drivers belonging to that class one by one. The time period defined as acceleration time for all members in the classes was determined and the engine capacity to reach maximum speed was determined by genetic algorithm so as to provide this time and not require the driver to make concessions from the driving comfort. At this point, it is necessary to pay attention to the use of the specific power of the motor to be presented to the driver is a solution for many of the problems mentioned before. For example, the use of 20 kW, 40kW and 60kW engines in the same vehicle results in a direct increase in the amount of carbon released into nature. Even though the production cost of the vehicle with these three engines does not change much, the vehicle with high engine power causes more carbon emission due to battery usage. Likewise, the amount of carbon emitted during the generation of the electricity used increases depending on the engine power. Although the emissions from the amount of gasoline used vary inversely with these values, when the total greenhouse gas emissions are considered, low engine power means low carbon emissions. Another advantage of the use of small engines is that the amount of battery that accompanies this engine is reduced, which is known to be the heaviest component in a vehicle. Already most of the optimization studies on electric cars are related to batteries. Therefore, a lighter vehicle and driver can achieve the same driving comfort due to the battery being reduced. When the annual cost is calculated for the three vehicles considered, there are large differences in points other than equal production costs. The price difference for these three vehicles due to the battery is expressed in thousands of dollars. The annual cost of a vehicle with a 20kW engine varies between $ 3600 and $ 4000 depending on the driving style, while the annual cost of a vehicle with a 40 kw engine varies between $ 4400 and $ 4600. These values are even higher when it comes to a 60 kW engine, ranging from $ 5100 to $ 5400. These changes are caused by driving patterns. Therefore, the difference in the price of users who use the same engine in different ways is seen. A larger engine means a larger battery, and the carbon-gas release during the production of these components is a significant difference when considering the more powerful engines.

In this thesis, the motor power values required for the three drive groups with genetic algorithm were found to be 25 kW for calm drivers, 65 kW for normal drivers and 185 kW for aggressive drivers. Without compromising the comfort and driving habits of the driver with the engine closest to these values among the cars available on the market, it can provide the most economical and environmentally friendly way to drive traffic. In this way, a significant improvement has been achieved both for the user and the environment.

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